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BUILDING A PREDICTIVE MODEL ON MATERNAL MORTALITY IN GHANA USING MACHINE LEARNING: COMPARISON OF DIFFERENT MODELLING TECHNIQUES

SARPONG GEORGE AMOFA

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BUILDING A PREDICTIVE MODEL ON MATERNAL MORTALITY USING MACHINE LEARNING: COMPARISON OF DIFFERENT MODELLING TECHNIQUES

BY

SARPONG GEORGE AMOFA

Dissertation submitted to the Department Data Science and Economic Policy of the School of Economics, College of Humanities and Legal Studies, University of Cape Coast in partial fulfillment of the requirements for the award of Master of Science degree in Data Management and Analysis

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DECLARATION

Candidate's Declaration

I hereby declare that with the exception of works from different authors which have been duly referenced, this dissertation was completed through my own original research effort. Therefore, no part of this project has been presented elsewhere by me or any other person for the award of another degree in the university or elsewhere.

Candidate's Signature ………………………… Date …………………...

Name: Sarpong George Amofa

Supervisors' Declaration

I hereby declare that the preparation and presentation of the dissertation were supervised in accordance with the guidelines on supervision of thesis laid down by the University of Cape Coast.

Supervisor's Signature ……………………… Date ………………........

Name: Dr. William Godfred Cantah

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ABSTRACT

Maternal mortality remains a critical public health issue in Ghana, influenced by complex socio-economic, health-related, and contextual factors. This study aimed to identify the most effective predictive modeling technique for maternal mortality and elucidate key risk factors. We developed and evaluated three predictive models: Logistic Regression, Random Forest, and Extreme Gradient Boosting (XGBoost) using data from the Ghana Maternal Health Survey (GMHS) 2017, which included 1,240 deceased women with detailed demographic, socio-economic, and health-related information. XGBoost emerged as the most robust and reliable model, achieving the highest average KFold score (0.8774), test accuracy (0.90), F1 score (0.47), and Jaccard score (0.82), indicating superior predictive performance. Significant predictors identified included place of death, marital status, blood pressure, traditional medication use, fever, season of death, and age at death. These findings highlight the need for targeted interventions to improve healthcare access, integrate traditional medicine into formal healthcare systems, and address socio-cultural barriers. Policy efforts should focus on enhancing healthcare access in rural areas, promoting gender equality in health decision-making, and targeting high-risk groups, particularly younger women and those with hypertension. Future research should include additional variables, conduct longitudinal studies, explore advanced machine learning techniques, and evaluate community-based interventions and policy impacts to further improve maternal health outcomes in Ghana.

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KEYWORDS

Maternal Mortality

Maternal Mortality Ratio

Verbal Autopsy

Random Forest Classification

Logistic Regression

Extreme Gradient Boosting (XGBoost)

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DEDICATION

I dedicate this project to God, my parents, family and also to my friends. Their unwavering love, support, and encouragement have been the foundation of my success. This work is a reflection of their belief in me and their constant inspiration.

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LIST OF ACRONYMS

CAPI	Computer Assisted Personal Interview
CHOs	Community Health Officers
CHPS	Community-Based Health Planning and Services
EAs	Enumeration Areas
GMHS	Ghana Maternal Health Survey
GSS	Ghana Statistical Service
LMICs	Low and Middle-Income Countries
MCHIP	Maternal and Child Health Integrated Programme
MMR	Maternal Mortality Ratio
NGOs	Non-Governmental Organization
NHIS	National Health Insurance Scheme
SDGs	Sustainable Development Goals
SES	Social Economic Status
SSA	South Saharan Africa
STIs	Sexually Transmitted Infections
WHO	World Health Organization

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CHAPTER ONE

INTRODUCTION

Introduction

This study aims to build a robust predictive model of maternal mortality and the associated factors in Ghana. The study will investigate the factors related to maternal mortality in Ghana as a whole. The present section examines the research's origins, issue statement, goals, and research questions. It also provides a justification for the study and examines its constraints and scope.

Background of Study

According to the World Health Organization's (1946) definition, health is a state of complete physical, mental, and social well-being in addition to the absence of disease or impairment. It acknowledges that achieving the best possible level of health is a major global societal aim that calls for the collaboration of the health sector as well as many other sectors of society and the economy, and that the right to health is an essential human right. Notwithstanding the fact that the global community has developed a number of methods to reduce maternal mortality, it continues to be a major public health concern. Maternal mortality is the most common reason for death for women who are 15 to 49 years old worldwide.

Improving maternal well-being is the fifth Millennium Development Goal, and the target is to cut the ratio of maternal deaths in half between 1990 and 2015. Nonetheless, maternal mortality has scarcely dropped in underdeveloped nations during the last decade, and in certain regions of Africa, it has climbed. Ghana aimed to reduce the rate of maternal deaths from

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740 per 100,000 births that survived in 1990 to 185 per 100,000 live births by 2015. Ghana's maternal mortality ratio (MMR) has decreased in recent years, from 560 deaths per 100,000 live births in 2005 to 451 deaths in 2007 (GHS, 2007). However, Kumasi records suggest that maternal fatalities continued to rise after then. Kumasi's MMR in 2007 was 359 per 100,000 live births, whereas it was 397 per 100,000 live births in 2008 (KMHD, 2009). The bulk of maternal fatalities in Kumasi (about 93%) happened at KATH, most likely due to the hospital's status as a referral center for difficult medical problems.

Ghana's maternal death ratio, at 380 per 100,000 live births, is still high, as it is in many other South Saharan African nations (WHO, 2019). According to data based on the 2017 Maternal Health Survey (GMHS) in Ghana, immediate maternity variables like postpartum hemorrhage, sepsis, pre-eclampsia, delivery difficulties, and improper abortion are thought to be directly responsible for approximately 75% of maternal deaths (GSS, 2018). The maternal medical literature in Ghana and other parts of Sub-Saharan Africa has frequently been emphasized; consequently, despite the fact that many of these major causes of maternal mortality are avoidable, women remain disproportionately vulnerable to perinatal problems and death as a result of inadequate access to professional treatment. Given this context, the Sustainable Development Goals (SDG) (indicator 3.1) reaffirmed the goal of achieving a worldwide maternal death ratio of fewer than 70 per 100,000 live births by 2030.

Ghana's rate of maternal death is high, similar to that of other developing nations. According to the Ghana Maternal Health Survey (GSS, 2018), Ghana's maternal mortality rate remained exceedingly high at 310

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deaths per 100,000 live births. A woman's risk for difficulties during pregnancy and childbirth can be increased by a number of conditions, including anemia, diabetes, malaria, sexually transmitted infections (STIs), and others. As a result, these disorders are indirectly responsible for mortality among mothers and hospitalization. Maternal health stakeholders in many LMICs have launched a variety of programs to boost survival and enhance maternal health outcomes in response to the new SDG goal. For example, health finance measures that lessen the cost of professional maternal healthcare have been implemented in Burkina Faso, Mali, Benin, and Morocco (Witter et al., 2016).

Specifically, Ghana has implemented a number of systematic efforts to increase the use of licensed maternity healthcare and reduce obstacles to access. These interventions include drone delivery of essential medical supplies, a Maternal and Child Health Integrated Programme (MCHIP), an initiative called Community-Based Health Planning and Services (CHPS), an exemption policy for expectant mothers from paying a fee under the National Health Insurance Scheme (NHIS), and the upgrading of community health nurses' skills to become certified Community Health Officers (CHOs) to improve management of complications during the gestation and delivery process (Ganle et al., 2014; Addo et al., 2018).

Notwithstanding the fact that these initiatives have typically increased access to first-rate maternity treatment, far less progress has been made in reducing the incidence of maternal fatalities in Ghana. The evaluation of maternal mortality in Ghana is predominantly dependent on estimates from institutional deaths, surveys of demography and health, and maternity

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indicator cluster surveys. This is because there are deficiencies in the implementation of efficient civil registration and vital statistics systems that facilitate the identification and categorization of deaths (GSS, 2018).

Statement of Problem

Giving birth ought to be a moment of life, not of death. And yet, problems from pregnancy and childbirth will have claimed the life of at least one woman by the time you finish reading this. During the year 2020, preventable causes associated with pregnancy and delivery claimed the lives of about 800 women every day, or one woman every two minutes (WHO, 2019).

Maternal mortality, which is defined as a woman dying during pregnancy, giving birth, or within 42 days of giving birth, is still a serious problem worldwide, particularly in middle- and low-income nations like Ghana. Despite numerous efforts, understanding and reducing the causes behind maternal mortality face significant challenges. Existing studies often focus on individual risk factors like inadequate prenatal care or socioeconomic status, overlooking the complex interactions between biological, social, economic, and healthcare-related variables. There's a crucial need for comprehensive research exploring these intricate factors.

Moreover, while predictive models are utilized, they often lack essential variables such as critical medical and mental health factors. Integrating these diverse factors into predictive models is essential for accurate understanding and application. Additionally, advanced machine learning techniques like Random Forest and XGBoost are underutilized in maternal mortality research. Exploring these methods can offer valuable insights into

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their effectiveness compared to traditional approaches. Bridging these gaps is vital for developing effective, holistic interventions in maternal healthcare.

Research Gap

Although maternal mortality has been extensively studied, most research focuses on direct medical causes and individual risk factors like healthcare access and socio-economic status, with limited attention to critical medical conditions and mental health factors, particularly in low-income countries like Ghana. Additionally, predictive models have predominantly relied on traditional statistical methods, often excluding advanced machine learning techniques such as Random Forest and XGBoost, which could improve accuracy. This study addresses these gaps by integrating cultural and mental health factors into predictive models and comparing traditional and machine learning approaches to enhance understanding of maternal mortality in Ghana.

Research Objectives

Consequently, the goal of this study is to determine which risk factor has the most impact on a pregnant woman's chance of dying during her pregnancy and in the days following delivery in Ghana, as well as to determine which model is best for forecasting maternal mortality. In particular, the research aims to:

1. To identify the most critical medical and mental health factors contributing to maternal mortality in Ghana.
2. To predict the probability of maternal death, based on a combination of medical, socio-economic, and mental health variables.

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3. To ascertain which approach is superior in terms of fit and predictive ability, compare the outcomes from both statistical procedures (Logistic Regression) and data mining techniques (Random Forest Machine Learning and Extreme Gradient Boosting).

Research Questions

1. What are the most significant medical, and mental health factors influencing maternal mortality in Ghana?
2. How can we predict the probability of maternal death using a combination of medical and socio-cultural variables?
3. How can the prediction of maternal mortality in Ghana be accomplished by a comparative analysis of modeling strategies such Logistic Regression, Random Forest Algorithm, and Extreme Gradient Boosting?

Significance of Study

For an assortment of reasons, predicting the likelihood of maternal mortality in Ghana and the wider globe has frequently been regarded as a crucial area of study in various academic fields. Firstly, precise forecasts of maternal mortality function as a tactical guide for many parties involved. They enable successful collaboration among demographers, planners, researchers, policymakers, and non-governmental organizations (NGOs), guaranteeing that resources are maximized, interventions are customized to the particular problems that communities face, and preventive actions are targeted. This cooperative strategy not only saves lives but also makes a substantial global and Ghanaian contribution to the general enhancement of maternal healthcare systems.

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A few of the factors that influence maternal mortality in Ghana will also be made clear by this study. Given that the impact is greatest in underdeveloped countries, maternal mortality is a serious problem. The anticipated worldwide maternal mortality rate (MMR) for 2020 was 223 per 100,000 live births, a decrease from 227 in 2015 and 339 in 2000. We will also be able to identify the important factors that influence maternal mortality in Ghana as a result of this study. Additionally, it will help us decide which modeling approach for maternal mortality is most appropriate. Ultimately, suggestions derived from the results would function as instruments for more investigation into the topic, guaranteeing the discovery of agreeable and enduring resolutions. The study's findings will also serve as a benchmark for the implementation of remedial actions aimed at reducing maternal mortality and raising public awareness.

Delimitation

This research focuses exclusively on maternal mortality data from Ghana. While this specificity allows for a more focused examination, it limits the findings' generalizability to other locations or countries. Maternal mortality rates in Ghana may be influenced differently than in other countries due to factors unique to the country's healthcare system, culture, and socioeconomic conditions. The study restricts its analysis to data from the 2017 Ghana Maternal Health Survey (GMHS). Because of the time constraint, the analysis is limited to the situations in Ghana that year. As a result, any advances or changes after 2017 are not considered, potentially altering the study's relevancy to the present maternal healthcare scene.

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The study restricts itself to using data from the GMHS 2017 dataset. While this dataset is comprehensive, ignoring other alternative data sources, such as local health records or qualitative interviews, may hinder a thorough understanding of maternal mortality. Alternative data sources may provide nuanced insights that add to the study's depth. The comparison of modeling strategies is limited to Logistic Regression, Random Forest Machine Learning, and Extreme Gradient Boosting (XGBoost) in the study. While these are advanced and frequently used methods, there are a plethora of different machine learning algorithms accessible. The study's analysis of the whole range of machine-learning technologies is hampered by the omission of these other techniques. Lastly, the analysis restricts its predictive model to the factors specified in the research goals. This emphasis gives the study a defined structure, but it excludes the investigation of any other variables that may influence maternal death rates. Factors that are not included in the defined covariates are not considered in the prediction model.

Limitations

Despite its value, the GMHS 2017 dataset can have temporal limitations. The healthcare infrastructure, socioeconomic circumstances, and maternal healthcare are all dynamic and subject to quick changes. It's possible that using data from 2017 will leave out the most recent advancements, legislative modifications, or advancements in healthcare that have happened in later years. The accuracy and applicability of the predictive model may be impacted by this time gap, which could result in forecasts that are inaccurate given Ghana's current state of maternal healthcare.

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Moreover, the scope and granularity of the dataset may not precisely match the needs of the study. It's possible that some vital variables that are required to create a thorough predictive model are absent from the GMHS 2017 dataset. This constraint may limit the research's ability to fully examine the range of factors that contribute to maternal mortality, which could result in an incomplete study and the possible overlooking of important determinants.

Definition of Terms

Maternal Mortality: Regardless of the length or location of the pregnancy, maternal mortality is defined as the death of a woman while she is pregnant or within 42 days of the pregnancy ending from any cause connected to or worsened by the pregnancy or its care, but not from unintentional or incidental causes.

Maternal Mortality Ratio: A crucial indicator in public health, the maternal mortality ratio counts the number of maternal deaths per 100,000 live births during a certain time frame. It offers a consistent method for calculating the risk of maternal mortality and evaluating the efficiency of healthcare systems and treatments for mother health.

Hemorrhage: Excessive bleeding, either internally or externally, that frequently stems from a disturbance in blood vessels is referred to as hemorrhage. Hemorrhage during pregnancy, labor, or the postpartum period is a major cause of maternal death in the context of maternal health. It may be linked to issues like postpartum hemorrhage, uterine rupture, or placental abruption; therefore, early medical attention is essential to avoid serious outcomes.

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Organization of Study

Five chapters make up the organization of the study. An introduction and study background are provided in the first chapter. This chapter provides a thorough explanation of the study's organization, including a number of important elements like the issue statement, study objectives, research questions, importance, and scope. Moreover, the second chapter provides its main focus, which is a thorough examination of the literature on maternal mortality. The approach used for the study is described in full in Chapter Three (3). It includes information about the research design, sample, data collection tool, and statistical methods that help meet the goals of the study. Data analysis and research presentation are covered in the fourth chapter (4). The conclusions and suggestions derived from the data are contained in the fifth and final chapter.

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CHAPTER TWO

LITERATURE REVIEW

Introduction

The purpose of this literature review is to offer an overview of important topics, proven risk factors, treatments, and obstacles associated with maternal mortality. The death of a mother, defined as the tragic loss of a woman's life during pregnancy, childbirth, or within 42 days of delivery, remains a serious global health issue. Despite substantial advances in medical research and healthcare infrastructure, maternal mortality still kills around 295,000 women globally each year, with the bulk of these fatalities happening in poor and middle-income countries (WHO, 2019).

This important worry reflects not just a failing in the healthcare system but also a sharp reminder of the socioeconomic inequities and gender inequalities that exist in many regions of the world. The significance of maternal mortality goes well beyond the acute loss of life. High maternal death rates have far-reaching consequences for families, communities, and nations. When mothers die, their children are more likely to suffer from hunger, lack sufficient schooling, and die at a younger age (Ronsmans et al., 2006). Furthermore, maternal mortality deprives society of the vital contributions made by women to their families and communities, prolonging a cycle of poverty and stifling socio-economic growth.

Theoretical Framework

Understanding the complicated issue of maternal mortality necessitates a sound theoretical framework that includes public health, sociology, economics, and healthcare administration. The Social Determinants of Health

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(SDH) model is one of the primary theoretical frameworks that guide research in this field. According to this perspective, health outcomes, including maternal mortality, are influenced by a multitude of societal, financial, and environmental factors, as opposed to just biological or medical causes. Several major components of the SDH framework are pertinent to maternal mortality research:

Socioeconomic Status (SES) and Maternal Mortality

Socioeconomic status (SES) plays a pivotal role in shaping maternal health outcomes and maternal mortality rates worldwide. SES encompasses a range of factors, including income, education, employment status, and access to resources. The impact of SES on maternal mortality is multifaceted, reflecting disparities in healthcare access, social support, and the capacity to make educated choices regarding reproductive well-being. Understanding the intricate relationship between SES and maternal mortality is crucial for developing targeted interventions and policies to reduce disparities in maternal healthcare.

Income disparities and financial barriers

Income is one of the strongest determinants of maternal health outcomes. Most women from low-income families face serious barriers in securing appropriate maternal healthcare. High out-of-pocket costs for services such as prenatal care, skilled birth attendance, and emergency obstetric services deter seeking timely care and greatly increase the risk of complications during pregnancy and childbirth (Garenne, 2015). Such financial barriers, where health insurance systems are either weak or nonexistent, may turn out to be a matter of life and death, especially among

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marginalized women. Unable to afford transport to health facilities, as well as fees for consultations, medicines, and hospitalization, they face an increased risk of dying from maternal causes (Filippi et al., 2006). Low-income women also tend to live in areas where health infrastructures are weak, marked by a scarcity of qualified healthcare professionals and a paucity of available services. This further predisposes these women to the greater risks of pregnancy and childbirth complications due to fatal delay (Ronsmans & Graham, 2006).

Education and health literacy

Education is another fundamental constituent of SES that strongly influences maternal mortality. Generally, women with more years of education possess better health literacy, which allows them to understand the importance of the services for maternal healthcare and recognize the warning signs for pregnancy complications. Educated women are more likely to receive prenatal care, follow medical advice, and deliver in health facilities capable of handling complications (Victora et al., 2010). They will also most likely practice family planning through spacing births appropriately and making beneficial choices about the use of contraceptives, thus contributing to improved health for themselves (Caldwell, 1986). On the other hand, less educated women are likely to have less information about basic maternal health practices, such as the necessity for appropriate care during birth by skilled professionals and the risks of home births without expert support (Gage, 2007). Such women are thus highly exposed to harmful cultural beliefs or superstitions that pose obstacles to seeking medical attention at modern hospitals due to reliance on such cultural practices, which may reduce levels of maternal mortality.

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Employment and Economic Security

The employment status of a woman closely relates to her access and ability to pay for healthcare services. Stable employment guarantees financial security, health insurance, and the capability to pay for maternal healthcare services that are necessary (Mundial, 2018). Women in formal employment have a higher likelihood of being covered by maternity leave and health benefits that sustain their well-being during pregnancy and childbirth. On the contrary, those women involved in the informal sector or low-wage jobs are usually not entitled to such benefits and have a disadvantage in pursuing quality maternal care (Benova et al., 2014). In many developing countries, women are highly represented in the informal economy, where jobs are insecure, low-wage, and lack social protection. Economic instability heightens women's vulnerability to maternal mortality because of limited access to timely and appropriate care (WHO, 2019).

Access to care and geographic inequality

SES also determines a geographical locality of residence, which is another important determinant of access to healthcare services. Poorer women tend to concentrate in rural or less privileged urban settings with an under-resourced and scant number of healthcare facilities for them to attend (Say & Raine, 2007). Geographic accessibility—characterized by distance to health centers, poor transport structures, and a general lack of emergency services—presents specific challenges in rural settings and distances individuals from care (Thaddeus & Maine, 1994). These delays result in poor maternal outcomes because complications like hemorrhage, infection, or eclampsia necessitate immediate medical attention (Say et al., 2014). Apart from these,

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lower SES women are less likely to receive full antenatal care and skilled birth attendance. In contrast, higher-SES women typically have access to better health services in private or better-funded public hospitals, where they can get timely and skilled care throughout pregnancy and delivery.

Social support networks and maternal autonomy

Other factors that can be influenced by SES include social support networks on which women will be relying for much-needed emotional, fiscal, and practical support through pregnancy and childbirth and which will be crucial in maternal health outcomes. Generally, a higher socioeconomic status means access to a greater amount of family, friends, and community resources that can offer the emotional, financial, and practical support needed. On the other hand, women of lower SES levels may have weaker social networks that leave them in isolation, unable to seek or advocate for the care they need. (Mundial, 2018) Socioeconomic status further dictates maternal autonomy, the extent to which a woman can independently make decisions regarding her health and well-being. Women of higher socioeconomic status are more likely to have full control over reproductive health decisions, such as when to seek care, where to deliver, or how to manage pregnancy complications. On the other hand, in the lower SES group, the women may experience stronger inhibitions on their autonomy, for example, pressure from family members, traditional gender roles, or financial dependency of women that can delay or prevent the seeking of appropriate maternal care.

Gender inequality and maternal mortality

Gender inequality is a widespread socioeconomic variable that has a major impact on maternal mortality rates, reflecting larger discrepancies in

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women's rights, social standing, and access to resources. Understanding how gender inequality relates to maternal mortality is critical for establishing targeted treatments and policies that empower women and enhance mother healthcare outcomes. Roles related to gender frequently affect family-making choice processes. Men have main decision-making authority in many civilizations when it comes to women's health, especially maternity healthcare. Women may lack autonomy in determining when and where to seek care, resulting in delays or insufficient healthcare usage, and the lack of autonomy might delay access to vital maternal healthcare treatments and contribute to maternal mortality (United Nations, 2019). These problems can be mitigated by empowering women to actively engage in healthcare decisions and teaching communities about the value of women's autonomy (Upadhyay et al., 2014).

Healthcare Access and Utilization

Women's access to healthcare can be hampered by gender discrimination. Women may encounter barriers such as cost, distance from healthcare facilities, and discriminatory practices within healthcare settings. In rare circumstances, healthcare personnel may fail to take women seriously, resulting in delayed or insufficient care. Gender disparities in healthcare access must be addressed in order to promote mother healthcare utilization and minimize mortality among mothers (WHO, 2019). In conclusion, tackling gender inequality is critical for improving the health of mothers’s outcomes and decreasing maternal rates of death. Women's decision-making power and healthcare usage may be increased by encouraging education, economic opportunity, and reproductive rights. Furthermore, addressing harmful

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sociocultural attitudes and practices, promoting gender-sensitive healthcare services, and guaranteeing equitable opportunities for women in all aspects of life are critical steps toward attaining gender equality and enhancing maternal healthcare worldwide.

Barriers to Healthcare Access

Geographic limitations like distance to healthcare facilities and a lack of transportation infrastructure can prohibit pregnant women from receiving appropriate prenatal care and emergency obstetric treatments in many places, particularly rural ones. The scarcity of healthcare facilities in distant places exacerbates these issues, resulting in delayed or insufficient maternal care (Thaddeus & Maine, 1994). Women are sometimes discouraged from accessing healthcare treatments due to financial restrictions. Direct expenditures, such as consultation, testing, and prescription fees, can be prohibitively expensive, particularly for low-income women. Indirect expenditures, such as transportation and lost income due to time away from work, add to the stress on families. Financial constraints can result in delayed or inadequate prenatal, birth, and postoperative treatment, increasing the risk of problems (Bohren et al., 2014). Cultural standards, societal shame, and gender biases can all influence women's healthcare decisions. Women's access to healthcare services and the sort of care they receive may be influenced by societal expectations and conventional beliefs. Discriminatory practices might discourage women from obtaining treatment even when services are accessible, resulting in negative maternal outcomes (Essendi et al., 2017).

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Improving Healthcare Utilization

Mobile clinics and community health workers, for example, can help bridge the gap between healthcare institutions and pregnant women, especially in rural regions. These interventions improve healthcare access and usage by providing key maternal health treatments, education, and support (Lassi et al., 2016). Comprehensive health education initiatives for women, families, and communities enhance awareness of the significance of maternal healthcare. These programs teach on prenatal care, safe birth procedures, and identifying danger indicators. Women who have been educated and are aware are more likely to seek healthcare, make informed decisions, and receive adequate treatment throughout pregnancy and delivery (Mbuagbaw et al., 2015). It is critical to strengthen healthcare systems through legislative efforts, infrastructural development, and healthcare practitioner training. Policies that enable universal access to important maternal health treatments, regardless of socioeconomic position, can enhance healthcare consumption dramatically. Adequate training for healthcare personnel in maternal care, respectful maternity care, and culturally competent practices is critical in order to deliver excellent services and foster confidence in healthcare institutions (Campbell et al., 2016).

In conclusion, reducing maternal mortality requires addressing barriers to healthcare access and usage. Countries may guarantee that all pregnant women have access to adequate maternal healthcare services by removing geographical, economic, cultural, and social barriers and adopting community-based initiatives, health education programs, and legislative changes. Empowering women with information, eliminating discriminatory behaviors,

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and building healthcare systems are all critical steps toward attaining equitable maternal healthcare access and, eventually, lowering worldwide maternal death rates.

Cultural and Social Norms Impact on Maternal Mortality

Maternal healthcare-seeking behavior is heavily influenced by cultural and social conventions, making them major predictors of maternal mortality rates. Cultural customs, traditional beliefs, and cultural expectations around pregnancy, delivery, and maternal care all have a substantial influence on women's decisions, frequently influencing their access to healthcare. Understanding these norms is critical for developing culturally appropriate interventions and policies to improve maternal health outcomes. Women's movement may be restricted by traditional gender norms, reducing their ability to attend healthcare services quickly. Hazardous behaviors, including female genital mutilation and child marriage, might raise the likelihood of difficulties during pregnancy and delivery, raising maternal mortality rates (World Bank, 2018). Traditional birthing customs are firmly ingrained in many cultures and impact how and where women give birth. Traditional birth attendants (TBAs) or older community women frequently help during childbirth. While these methods are culturally based, they may lack the requisite medical knowledge and abilities, resulting in problems and maternal death. To address these behaviors, communities must be sensitively educated on the necessity of trained birth attendants and easily accessible healthcare facilities (Koblinsky et al., 2006).

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Religious Beliefs and Superstitions

Maternal healthcare can be influenced by religious beliefs and cultural practices. Some religious customs, such as menstruation, may limit a woman's capacity to receive healthcare or impose nutritional restrictions during pregnancy. Understanding and honoring cultural customs while maintaining crucial maternal health care is critical. Engaging religious and community leaders as maternal health advocates can help to create acceptance and support proper care-seeking behavior (Ahmed et al., 2010). Traditional beliefs and superstitions about pregnancy, delivery, and maternal health practices can have an impact on healthcare-seeking behavior. Some societies may attribute difficulties to supernatural origins, resulting in a dependence on traditional healers or the postponement of medical measures. Sensitization efforts must address these views by debunking myths about contemporary healthcare methods and presenting factual information about the benefits of modern healthcare practices (Essendi et al., 2017).

Stigma and prejudice associated with pregnancy before marriage, adolescent pregnancies, or problems following childbirth might discourage women from seeking medical attention. Some women avoid prenatal and maternity care because they are afraid of being judged or facing societal reaction. To overcome these cultural preconceptions, it is necessary to challenge stereotypes and provide inclusive and non-discriminatory healthcare facilities in which all women feel secure and valued (Bohren et al., 2014).

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Empowerment and Agency; Catalysts for Maternal Healthcare Improvement

Empowerment and agency are critical ideas in maternal healthcare, impacting women's ability to make health and well-being decisions. Women who have agency have the information, skills, and confidence to navigate healthcare systems, make educated decisions, and advocate for their maternal health needs. Understanding the importance of empowerment and agency is critical for improving maternal health outcomes and lowering maternal mortality rates. Knowledge is the first step toward empowerment. Women who have received an education and are knowledgeable are extremely likely to realize the value of maternal healthcare services, including prenatal therapy, skilled delivery attendance, and postnatal support. Education provides women with the knowledge they need to comprehend pregnancy-related hazards, identify danger indicators, and seek prompt medical attention. Informed women can actively engage in healthcare decision-making processes, increasing their total agency (Babalola & Fatusi, 2009).

Financial freedom enables women to seek healthcare without relying on the resources or authorization of others. Women with economic clout can pay for medical consultations, transportation to healthcare institutions, and prescriptions. Economic empowerment also gives women a sense of autonomy, allowing them to make health-related decisions without financial limitations restricting their options (Ahmed et al., 2010). Healthcare agency refers to a woman's capacity to efficiently navigate the healthcare system. It involves the ability to speak with healthcare practitioners, ask questions, and express preferences for medical procedures.

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During pregnancy, labor, and delivery, women with healthcare agencies actively engage in decision-making, ensuring that their healthcare requirements and preferences are met. The role of healthcare agencies in encouraging pleasant birthing experiences and increasing mother satisfaction with healthcare services is critical (Davis-Floyd & Barclay, 2019). Women who are empowered may speak not only for their personal health but also for the health of their communities. Women are empowered when they have the confidence to educate others about maternal health, question harmful customs, and push for better healthcare services. Empowered women frequently serve as community leaders, raising awareness, organizing resources, and advocating beneficial maternal health practices (Sharan & Valente, 2002).

In maternal healthcare, empowerment and agency are transforming factors. Societies may break down obstacles that hinder women from receiving vital maternity healthcare services by providing them with education, financial freedom, decision-making autonomy, healthcare agency, and community support. Women who are empowered not only protect their own well-being, but they also contribute significantly to decreasing maternal mortality rates, developing healthier communities, and advocating for structural improvements in maternal healthcare systems.

Empirical Review

Maternal Mortality Ratio; A Crucial Focus for Maternal Health Studies

The Maternal Mortality Ratio (MMR) is an essential maternal health statistic that serves as a focus point for empirical evaluation and research. MMR, known as the proportion of maternal fatalities per 100,000 live births within a particular period of time, gives significant information on the

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effectiveness of healthcare systems, the impact of efforts, and the overall well-being of women throughout pregnancy and childbirth. Several empirical studies have looked into different elements of MMR, shed light on disparities, identified risk factors, and evaluated healthcare remedies. This essential indicator has been instrumental in guiding policy decisions, identifying programs, and advancing global progress toward maternal mortality reduction.

Researchers have used longitudinal studies of MMR data to track changes over time and examine discrepancies within and across areas. Research works such as those undertaken by Hogan et al. (2010) and Alkema et al. (2016) have offered valuable insights into shifting patterns of maternal mortality, allowing policymakers to effectively focus resources and implement interventions where they are most needed. The experimental investigation has examined the impact of several treatments on MMR reduction, including skilled birth attendance, availability of emergency obstetric care, and community-based maternal health programs. Bhutta et al. (2014) and Campbell et al. (2016) completed research works that proved the effectiveness of targeted treatments in decreasing maternal death rates, providing significant evidence for policymakers and healthcare practitioners.

Lastly, MMR has been used by researchers to assess the efficiency of health-system strengthening programs. Kruk et al. (2015) gave critical insights into the significance of health system elements in maternal mortality reduction by analyzing the preparedness of healthcare facilities, availability of qualified staff, and accessibility of emergency obstetric services.

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Maternal Mortality Rate

These measures the number of women who tragically die within 42 days after the end of their pregnancy. These fatalities are especially related to issues that occur during pregnancy, delivery, or the postpartum period, sometimes known as the puerperium. To compute this ratio, we divide the total number of maternal fatalities in a particular geographical region, in this case the nation of Ghana, by the total number of live births reported in the same area for a specific time period, often a calendar year. This value is then multiplied by 100 to provide a ratio per 100 live births, which gives a more complete view of the maternal health landscape in that location.

Calculation of Maternal Mortality

$$Maternal\ Mortality\ Rate$$

$$= \frac{Number\ of\ resident\ maternal\ deaths}{Number\ of\ resident\ live\ births} \times 100$$

The World Health Organization (WHO) provides a thorough definition of the death of a mother, which includes the sad loss of a woman's life during pregnancy or during a critical period of 42 days after the termination of her pregnancy. This term is all-inclusive, regardless of pregnancy duration or location. It includes deaths caused by any issues directly related to pregnancy or its medical care. However, it specifically excludes fatalities caused by external, unintentional, or incidental circumstances unrelated to the pregnancy.

The International Classification of Diseases, Tenth Revision (ICD-10) uses particular codes to identify these sad events. These codes serve as a common language for healthcare practitioners and academics worldwide, allowing for uniform and accurate documentation of maternal fatalities. The pertinent codes are A34, which reflects obstetrical tetanus, and a sequence of

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numbers ranging from O00 to O95 and O98 to O99. These later codes include a wide range of diseases, including ectopic and molar pregnancies (O00-O08) and various obstetric difficulties that can occur during pregnancy, labor, delivery, and the postpartum period. The WHO and healthcare systems throughout the world may use these codes to monitor, research, and eventually work toward lowering maternal mortality, guaranteeing safer pregnancy and delivery experiences for women around the globe.

There are significant issues concerning the accuracy and uniformity of representation among nations in terms of maternal mortality, with evidence of significant fluctuation in rates across nations. Some of these disparities have been linked to maternal mortality underreporting, particularly when maternal mortality is diagnosed primarily through death certificates. Maternity mortality results may vary because they are derived from places other than death certificate records. These sources include reports on pregnant women's mortality surveillance, the conclusions of boards within the health departments of states that review suspected maternal deaths regularly, and the routine linking of deaths among women of gestational age to files pertaining to live births and embryonic tissue deaths.

In 2003, a redesigned death certificate was produced as the model certificate, and it included a new entry on the pregnant status for dead females in order to increase the completeness and comparability of maternal mortality statistics across the country. Beginning in 2004, when states implemented the updated death certificate, the number of maternal fatalities detected increased. The maternal death rate, also known as the ratio of maternal deaths, is calculated without a precise count of all pregnancies that might result in a

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mother's death, with stillbirths eliminated and children derived from various birth sets disproportionately represented in live birth statistics. Maternal mortality rates may be regarded as too unstable or inaccurate for study if the number of maternal fatalities per year is modest (<10 or 20). Maternal mortality rates may be regarded as too unstable or inaccurate for study if the number of maternal fatalities per year is modest (<10 or 20).

Adding extra years (three or five-year average yearly rates) and/or enlarging the study region should result in a greater number of fatalities and more accurate rates for analysis. Late maternal fatalities occur more than 42 days after the pregnancy is terminated but less than one year later. Pregnancy-associated fatalities occur for any reason during or within a year of gestation after birth or termination, regardless of pregnancy duration or geographical location. Pregnancy-related fatalities include not just those frequently connected with pregnancy, such as bleeding, high blood pressure caused by pregnancy, and thromboembolism (as defined by the WHO), but also deaths that are not traditionally associated with pregnancy, such as accidents, homicide, and suicide.

Maternal mortality and the sustainable development goal (3)

Maternal mortality, a harsh reality for many women throughout the world, is a difficult hurdle to attaining sustainable development. The terrible specter of maternal death throws a shadow among the tremendous joys of parenting, reminding us of the urgent need for radical change. Maternal health is central to the third goal of the Sustainable Development Goals (SDG 3) and strives toward ensuring healthy lifestyles and enhancing good health for all people of every stage of life (United Nations, 2015). SDG 3 demands a radical

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transformation in our approach, an unrelenting commitment to protecting the lives of mothers and nurturing future generations.

SDG 3 acts as a light of hope and resolve in the midst of this global disaster. The United Nations has sparked a powerful movement by establishing a target of less than 70 maternal deaths per 100,000 live births by 2030 (United Nations, 2015). This target is more than simply a statistic; it represents the promise of a safer, healthier future for women worldwide. It forces governments to invest in solid healthcare infrastructures in order to ensure that every expecting woman receives the best treatment she deserves. The fight against maternal mortality goes beyond hospitals and clinics; it pervades populations and necessitates a cultural revolution. It encourages communities to empower women by offering education, autonomy, and access to healthcare (UN, 2015).

It pushes healthcare practitioners to constantly improve their abilities, embrace innovation, and provide compassionate treatment. Most importantly, it encourages every one of us to be change agents, raising our voices to shatter the silence around maternal death. Consider the stories of resilience shared by women who have overcome adversity to properly comprehend the scale of this problem and the transforming impact of SDG 3. Consider the communities that have banded together to establish birthing facilities, give information, and break down barriers that formerly claimed lives. These frequently unheard stories exemplify the spirit of SDG 3 in action, demonstrating the limitless potential of collaborative efforts.

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Direct maternal causes of death

An important area of empirical study in maternal health is direct maternal causes of death, which include concerns linked to pregnancy, childbirth, and the postpartum period. Understanding these characteristics is crucial for developing effective therapies and strategies to lower maternal mortality rates worldwide. Experimental discoveries have delved deep into these direct causes, providing insight into their prevalence, trends, and determinants, therefore directing evidence-based maternal mortality prevention efforts.

Hemorrhage, which is frequently induced by postpartum hemorrhage, is the biggest direct cause of maternal death. Khan et al. (2017) investigated the incidence of hemorrhage-related fatalities, highlighting the significance of prompt treatments such as competent delivery attendance and availability to emergency obstetric care to prevent fatal outcomes. Infections, such as sepsis and puerperal fever, continue to be major causes of maternal death. Empirical research (Say, 2014) has underlined the relevance of infection prevention methods during labor and postpartum care in reducing the frequency of infection-related maternal mortality.

Hypertensive diseases, such as pre-eclampsia and eclampsia, are major causes of maternal death. To avoid maternal mortality, research (Abalos et al., 2013) has stressed the need for frequent prenatal check-ups, early identification, and effective management of hypertension throughout pregnancy. Unsafe abortion is a direct cause of maternal death that may be avoided. Empirical research (Ganatra et al., 2017) has looked into the

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influence of safe abortion services, comprehensive sexuality education, and family planning programs on maternal mortality caused by unsafe abortions.

Maternal mortality and the Millennium Development Goal (5)

Maternal mortality has been a focus of the Millennium Development Goals (MDGs), notably Goal 5, which is intended to enhance maternal health. The Millennium Development Goals (MDGs), established by the United Nations in 2000, had an important influence in developing global health policies and activities. Goal 5 particularly called for a 75% decrease in maternal mortality rates by 2015, as well as universal access to reproductive healthcare services. Empirical research on MDG 5 development has offered useful insights into the obstacles faced, gains gained, and lessons learned in the field of maternal health.

Investigative studies evaluated the progress made toward the MDG 5 objectives in a methodical manner. Hogan et al. (2010) conducted a comprehensive review of maternal mortality data from 1980 to 2008 in 181 countries. This research not only showed global differences in maternal death rates, but it also analyzed progress toward MDG 5 objectives. Empirical research examined the effectiveness of various strategies used to lower maternal mortality rates. Campbell et al. (2016) analyzed the impact of initiatives like expert birth participation, access to urgent obstetric treatment, and pregnancy prevention services. These assessments helped me understand the actual consequences of MDG-5-aligned actions.

Rigorous research revealed the obstacles and barriers impeding MDG-5 development. Ahmed et al. (2010) investigated the socioeconomic factors of maternal health service usage, such as economic status and education.

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Understanding these issues was critical for devising focused treatments to address inequities. Empirical studies have also assessed MDG 5's legacy in shaping post-MDG activities including the Sustainable Development Goals (SDGs). Assessments of the influence of MDG 5 on the creation of SDG 3.1, which seeks to lower the global maternal death ratio to less than 70 per 100,000 live births by 2030, have offered crucial insights into the continuity of maternal health initiatives.

Conceptual Framework

Building a maternal mortality prediction model entails creating a conceptual framework that explains the important elements impacting maternal health outcomes. The conceptual framework that follows gives an organized way to developing such a model:

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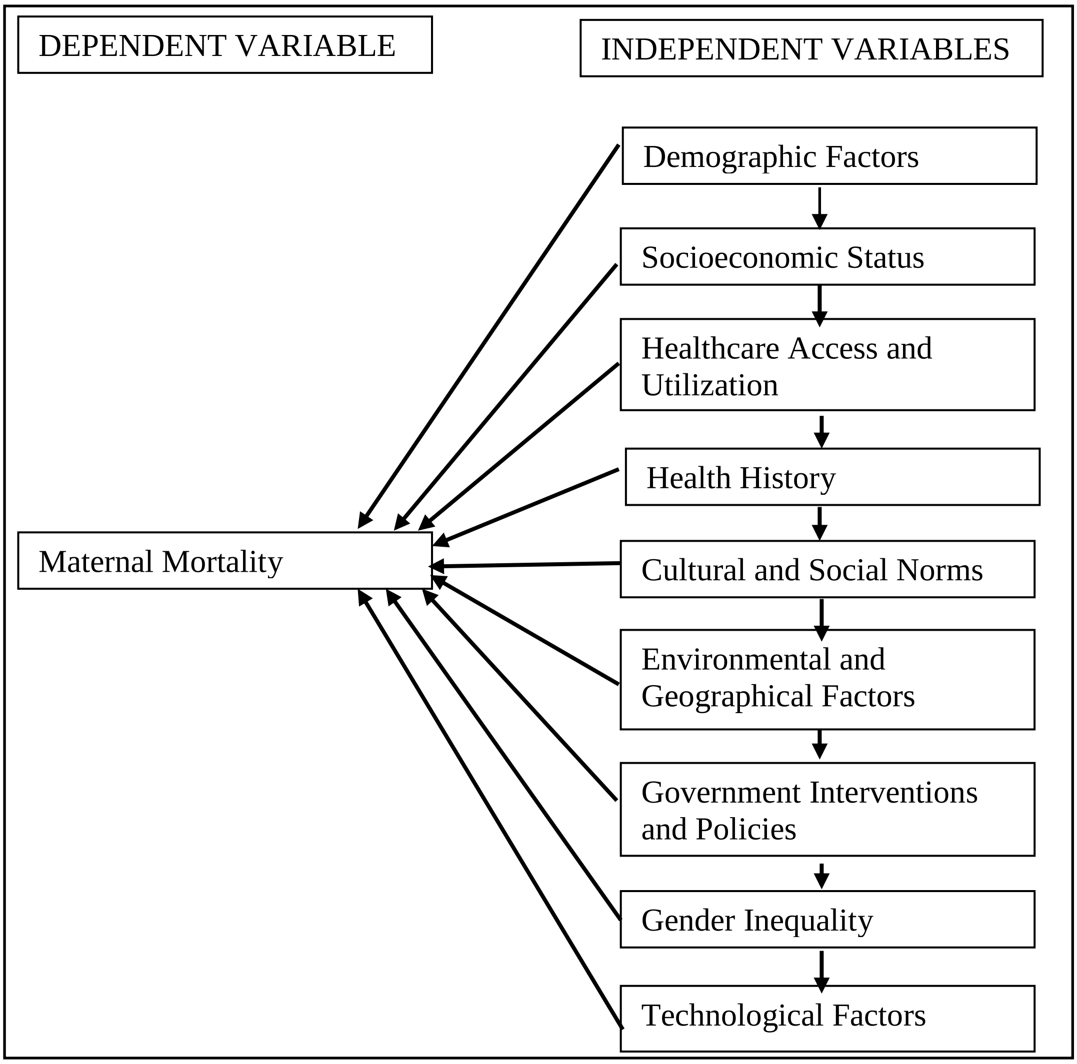

Figure 1: Conceptual Framework

Source: Author (2024)

Chapter Summary

In general, this section of the book research work offers a thorough survey of the available literature, bringing readers through the historical, theoretical, and empirical terrain pertinent to these studies. It highlights gaps, controversies, and trends, giving context for the coming chapters and explaining the relevance and uniqueness of the study within the academic arena.

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CHAPTER THREE

RESEARCH METHODOLOGY

Introduction

The current section provides a full description of the research approach used to investigate the suggested research question. It carefully describes the provenance and nature of the data used, offering insights into the individual datasets and their significance to the study. The chapter goes further into the analytical approach, including the methodologies and processes used to critically review the data. This contains a discussion of the various statistical methods and procedures utilized, emphasizing how they contribute to the reliability and validity of the study findings. The chapter sought to provide a full grasp of the investigative framework, emphasizing the rigor and accuracy used to handle the research challenge at hand.

Research of Design

The research will use a positivism philosophy; in this design, we concurrently collect quantitative data, analyze them, and then compare or connect the results. The quantitative component makes use of secondary data, such as existing databases, records, or historical data, which may be quantitatively evaluated to uncover patterns, trends, or linkages. This technique provides a wide numerical grasp of the research problem.

Data Source and Type

The verbal autopsy data was used for this research. The data used for the research is secondary data from the Statistical Service website; the survey is labeled as the Ghana Maternal Health Survey (GMHS) 2017. After the 2007 GMHS, the 2017 GMHS is the nation's second nationwide representative

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household survey that gathers detailed data on maternal health concerns, mortality rates for mothers, and particular causes of death among women. There were two stages to the survey that collected data on maternal health. Thousand nine hundred (1900) enumeration areas (EAs) were chosen in Phase 1 (466 in urban and 434 in rural regions).

Every household in the chosen clusters was noted, and homes where a woman between the ages of 12 and 49 had passed away since January 2012 were additionally marked for a verbal autopsy. Phase 2 involved interviewing 26,324 households with 25,062 eligible women aged 15-49 about a variety of maternal health-related topics, including pregnancies, live births, terminations of pregnancy (abortion), miscarriages, and the use of health services in connection with these events. The sibling history of the women interviewed was also recorded, which makes it possible to calculate Ghana's maternal death rate. The Verbal Autopsy Questionnaire was employed to gather data necessary for identifying the cause(s) of death for 1,240 women, aged 12-49, who passed away within the five years before the Phase 1 survey (GSS, 2018).

Study Variables

Predicted Variable

The predicted variable that was studied in this research was "maternal mortality." Byposing a question regarding every one of the 1240 women's deaths, this variable is extracted from the verbal autopsy dataset. Whether their female relative died as a result of "death during pregnancy, delivery, or within 42 days or one year of the end of pregnancy?" was one of the questions asked of relatives, spouses/husbands, friends, and siblings during the verbal autopsy survey. To this question, there were two main responses: We

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categorized all yes answers as maternal mortality and all no replies as non-maternal mortality in order to facilitate the interpretation of our study. There were two possible outcomes for our final outcome variable, maternal mortality: yes (maternal death) and no (non-maternal death). One was assigned to maternal deaths and zero to non-maternal deaths in the recoded results.

Predictor Variable

Based on prior research on maternal health outcomes, the following pertinent variables were selected and appropriately recoded: age at death, highest level of education attained, marital status, occupation, religion, place of death, infection with malaria, HIV, and AIDS, use of traditional/herbal medicine during pregnancy, primary mode of transportation during healthcare-seeking prior to death, residence, season of death, birth attendant in most recent delivery, location of most recent birth, and for mental health we had, depression and mental disorder.

We included in our analysis other factors related to the sickness features of the women, such as bleeding or hemorrhage, diabetes mellitus, cancer, abdominal or ovarian mass, fever, high blood pressure, and many more. However, there was missing data for a number of variables, including "occupation," "primary mode of transportation," "birth attendant," and "location of most recent birth." Other variables included "bleeding during pregnancy," "had excessive bleeding during labor or delivery, during pregnancy," high blood pressure, a malaria test, and "discharged from hospital very ill." The study kept some of the dataset's independent variables coded according to their original conventions.

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Data Processing and Analysis

The collected data underwent a rigorous processing regimen. Initial steps involved data registration, consistency checks, and outlier identification. Subsequently, a comprehensive data editing and cleaning process was employed to ensure accuracy and completeness. Secondary editing was performed, addressing questions that are open-ended with coding and computer-identified discrepancies. The utilization of STATA and Python software, a trusted tool in the field of data processing, facilitated these operations. This meticulous approach resulted in a high-quality dataset ready for in-depth analysis.

In the analysis of maternal health variables, notable discrepancies in sample sizes were observed due to missing values. The variable “Transport Means” had a higher sample size of 833, indicating women’s willingness to discuss transportation methods, which are vital for accessing healthcare. In contrast, “Place of Birth and Professional Assistance” had significantly lower sample sizes of 125 each, suggesting stigma around non-institutional births may hinder disclosure. Additionally, the variables “Abortion Attempts” (n = 254) and “Previous Caesarean Section” (n = 192) showed reductions likely due to the sensitive nature of these topics, leading to underreporting. Similarly, “Bleeding During Pregnancy” and “Pregnancy Miscarried” also had lower sample sizes (n = 254), reflecting societal hesitance to discuss these issues.

Logistics Regression

Logistic regression is a form of mathematical modeling for describing the relationship between many predictor factors and a dichotomous dependent variable. It is intended especially for scenarios in which the predicted variable

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(outcome) is classified and has two potential values, often represented by the codes 0 and 1. In contrast to linear regression, which forecasts a continuous result, logistic regression uses the logistic function (sometimes called the sigmoid function) to represent the connection between the categorical dependent variable and the independent factors. This function is appropriate for binary classification jobs since it guarantees that the expected probabilities fall between 0 and 1.

Origins and intuition of logistic regression

Belgian mathematician Pierre François Verhulst developed the logistic function in the middle of the 1800s as a method for estimating population growth in people, animals, and various plant and fruit species (McNulty, 2021). By now, it was well accepted that there was a maximum population number that could be achieved due to resource and environmental limits as well as the fact that population growth could not continue endlessly. Verhulst's function has the following formula:

$$\boldsymbol{y = \frac{L}{1 + e^{-k(x-x_0)}}}$$

where $\boldsymbol{L}$ is the highest possible value of $\boldsymbol{y}$ (sometimes defined as the "carrying capacity" and generally 1), $\boldsymbol{k}$ is the maximum slope of the curve, $\boldsymbol{e}$ is the exponential constant, and $\boldsymbol{x_0}$is the value of $\boldsymbol{x}$ at the midway. With slower growth in the starting stage, exponential growth in the intermediate phase, and reduced growth as the population approaches it carrying capacity, the logistic function, which is shown in Figure 2, was deemed to appropriately describe the projected stages of population expansion.

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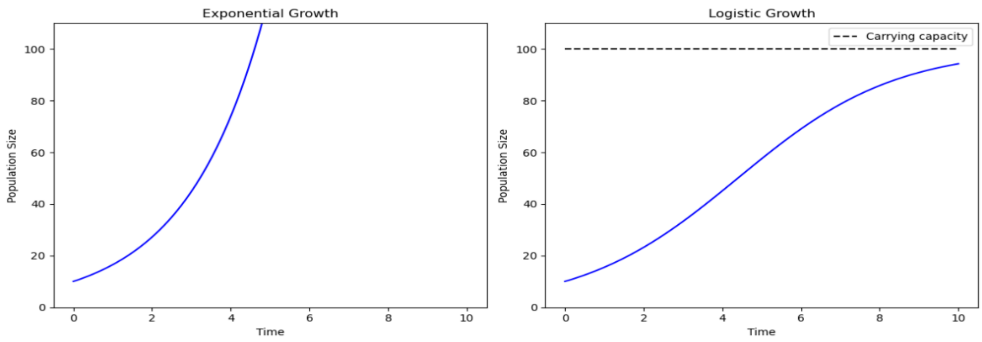

Figure 2: The exponential nature of population increases as well as its natural limit were both represented by Verhulst's logistic function

Source: Author (2024)

In the first part of the 20th century, the logistic function was initially used in chemistry and economics, and it quickly gained acceptance as a useful tool for explaining events in a variety of fields. In statistics, standard deviations around a mean are reflected on the x-axis (Time) scale, and the logistic function has an S-shape (also called sigmoid) similar to a cumulative normal distribution of probability.

Deriving the concept of log odds

Let's take a closer look at the value of the index of the exponential constant $\boldsymbol{x}$ in our logistic function's denominator. Keep in mind that since $\boldsymbol{x_0}$ is a constant, we have:

$$-\boldsymbol{k}(\boldsymbol{x}-\boldsymbol{x_0}) = -(-\boldsymbol{kx_0}+\boldsymbol{kx}) = -(\boldsymbol{\beta_0}+\boldsymbol{\beta_1 x})$$

where $\boldsymbol{\beta_0} = -\boldsymbol{kx_0}$ and $\boldsymbol{\beta_1} = \boldsymbol{k}$.

Therefore,

$$\boldsymbol{P}(\boldsymbol{y}=\mathbf{1}) = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e}^{-(\boldsymbol{\beta_0}+\boldsymbol{\beta_1 x})}}$$

This equation seems to make sense. When $\boldsymbol{x}$ grows, the value of $\boldsymbol{e}^{-(\boldsymbol{\beta_0}+\boldsymbol{\beta_1 x})}$ decreases until it reaches zero, bringing $\boldsymbol{P}(\boldsymbol{y}=\mathbf{1})$ closer to its hypothetical maximum value of 1. We see that the value of $\boldsymbol{P}(\boldsymbol{y}=\mathbf{1})$ approaches a

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minimal value of $\frac{1}{1+e^{-(\beta_0)}}$ when the value of x drops towards zero. With reference to our verbal autopsy data, we can thus see that, under the assumption that all variables are zero, β_0 aids in determining the baseline likelihood of maternal death. This baseline probability will reach its theoretical minimum of zero if β_0 has an exceptionally negative value.

Let us formalize the contribution of β_0 and β_1 to the probability of a favorable result. As far as we are aware, any dichotomous event y, $P(y = 0)$ is equal to $1 - P(y = 1)$, so

$$P(y = 0) = 1 - \frac{1}{1 + e^{-(\beta_0+\beta_1 x)}}$$

$$= \frac{1 + e^{-(\beta_0+\beta_1 x)} - 1}{1 + e^{-(\beta_0+\beta_1 x)}}$$

$$= \frac{e^{-(\beta_0+\beta_1 x)}}{1 + e^{-(\beta_0+\beta_1 x)}}$$

putting these together, we find that;

$$\frac{P(y = 1)}{P(y = 0)} = \frac{\frac{1}{1 + e^{-(\beta_0+\beta_1 x)}}}{\frac{e^{-(\beta_0+\beta_1 x)}}{1 + e^{-(\beta_0+\beta_1 x)}}}$$

$$= \frac{1}{e^{-(\beta_0+\beta_1 x)}}$$

$$= e^{\beta_0+\beta_1 x}$$

Alternatively, if we take both sides' natural logarithms

$$ln\left(\frac{P(y = 1)}{P(y = 0)}\right) = \beta_0 + \beta_1 x$$

$P(y = 1)$ is the likelihood that the event will happen, and $P(y = 0)$ is the likelihood that it won't. We may be aware that the proportion of these two indicates the probability of an occurrence from sports like horse racing or other gambling scenarios.

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Maximum Likelihood (ML) Estimation

One statistical method for estimating the variables in a mathematical model is maximum likelihood (ML) estimation. The variables that make up the parameters of a logistic model were estimated via discriminant function analysis before computer software for ML estimation became available. The parameters of a logistic model can be estimated using one of two machine learning approaches. These approaches are referred to as conditional and unconditional. Different computer programs must be used for these two approaches.

When choosing between unconstrained and conditional ML approaches, the researcher must consider the number of parameters in the model relative to the total number of participants under consideration. In general, unconditional machine learning (ML) estimation is selected when the model's parameter count is small relative to the total number of people. On the other hand, conditional machine learning estimation is advised in situations when the model's parameter count is significant relative to the number of subjects. To clarify the ML method, $\boldsymbol{L}$, the likelihood function, is introduced. Another way to express the probability function is as $\boldsymbol{L}(\boldsymbol{\theta})$. The total probability or likelihood of witnessing the gathered data is represented by the likelihood function $\boldsymbol{L}$, also known as $\boldsymbol{L}(\boldsymbol{\theta})$. The probability of a dichotomous logistic regression model being successful for a sample size n is provided by:

$$\boldsymbol{L}(\boldsymbol{\beta};\boldsymbol{y},\boldsymbol{X}) = \prod_{i=1}^{n} \boldsymbol{\pi}_i^{y_i}(\mathbf{1}-\boldsymbol{\pi}_i)^{1-y_i}$$

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$$= \prod_{i=1}^{n} \left(\frac{\exp(X_i\beta)}{1+\exp(X_i\beta)} \right)^{y_i} \left(\frac{\exp(X_i\beta)}{1+\exp(X_i\beta)} \right)^{1-y_i}$$

This yields the log likelihood:

$$\ell(\beta) = \sum_{i=1}^{n} [y_i \log(\pi_i) + (1-y_i)\log(1-\pi_i)]$$

$$= \sum_{i=1}^{n} [y_i X_i \beta - log(1+\exp(X_i\beta))]$$

Since there isn't a closed-form answer for maximizing the likelihood (or log-likelihood), an approach similar to progressively reweighted least-squares estimation is employed to estimate the regression coefficients, $\hat{\beta}$.

Odds, Log Odds, and Odds Ratio

A measure of the correlation between an exposure and an outcome is the odds ratio (OR). In contrast to the likelihood that the result will occur in the absence of that exposure, the OR shows the chance that an event will occur given a certain exposure. Although odds ratios are most typically employed in case-control studies, they can also be utilized in cross-sectional and cohort studies. The regression coefficient β_1 in a logistic regression is the projected rise in every unit increase in the value of the quantity of exposure in the log odds of the result. In other words, the ratio of odds corresponding to an increase in the regression by one unit gives the coefficient's exponential function as e^{β_1}.

The Log Odds

$$Odds = log\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k,$$

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The termed "log odds" indicate that the (natural) logarithm of the odds is a linear function of the X variables. The logit transformation of the success probability, *P*, is another name for this.

The odds ratio, denoted as θ, comparing the odds of two sets of predictors, such as $X_{(1)}$ and $X_{(2)}$, is found by

$$\boldsymbol{Odds\ Ratio}\ (\boldsymbol{\theta}) = \frac{(\boldsymbol{P}/(\mathbf{1}-\boldsymbol{P}))|_{\boldsymbol{X}=\boldsymbol{X}_{(\mathbf{1})}}}{(\boldsymbol{P}/(\mathbf{1}-\boldsymbol{P}))|_{\boldsymbol{X}=\boldsymbol{X}_{(\mathbf{2})}}}$$

The following are the success odds for binary logistic regression:

$$\frac{\boldsymbol{P}}{\mathbf{1}-\boldsymbol{P}} = \mathbf{exp}(\boldsymbol{X}\beta)$$

By substituting this information into the **θ** formula and ensuring that $\mathbf{X}_{(1)}$ equals $\mathbf{X}_{(2)}$ we can determine the relationship between that particular predictor and the response variable, with the exception of one location (where just one predictor varies by one degree). The odds ratio, a positive number, can vary widely. An odds ratio of 1 act as the reference point, indicating no relationship between the response and the predictor. When the odds ratio exceeds 1, it signifies higher success odds associated with elevated levels of a continuous predictor (or with a specified level of a categorical variable). Specifically, the odds increase exponentially by a factor of $\mathbf{exp}(\beta_j)$ for every one-unit rise in $\mathbf{X}_j$**.** On the other hand, lower success probabilities for higher levels of a continuous predictor (or for the designated level of a categorical variable) are indicated if the odds ratio is less than 1. Stronger degrees of connection are indicated by values that substantially deviate from 1. For example, if there is just one predictor, X, the probability of a successful outcome is:

$$\frac{\boldsymbol{P}}{\mathbf{1}-\boldsymbol{P}} = \mathbf{exp}(\beta_0 + \beta_1\boldsymbol{X})$$

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If we increase X by one unit, the odds ratio becomes

$$\boldsymbol{\theta} = \frac{\mathbf{exp}(\beta_0 + \beta_1(\boldsymbol{X} + \mathbf{1}))}{\mathbf{exp}(\beta_0 + \beta_1 \boldsymbol{X})} = exp(\beta_1)$$

Variance Inflation Factor (VIF)

In logistic regression and other regression models, the variance inflation factor (VIF) is a diagnostic tool used to examine multicollinearity among predictor variables. Assessing the relative contributions of each predictor variable in a regression model becomes challenging when two or more of the variables are strongly correlated. By measuring the extent to which predictor correlation exaggerates the variance of the predicted regression coefficients, VIF measures the degree of multicollinearity.

Calculation of VIF

For each predictor variable in the logistic regression model, the VIF is calculated using the formula:

$$\boldsymbol{VIF_i} = \frac{\mathbf{1}}{\mathbf{1} - \boldsymbol{R_i^2}}$$

where $\boldsymbol{VIF_i}$ is the Variance Inflation Factor for the $i - th$ predictor. $\boldsymbol{R_i^2}$ and $\boldsymbol{R}^2$ value obtained by regressing the $i - th$ predictor against all other predictors in the model.

Interpretation:

- **VIF = 1:** No multicollinearity. The variance of the estimated regression coefficients is not inflated.
- **VIF > 1 and < 5**: Moderate multicollinearity. Predictor variables have some relationship with one another, although it might not be strong enough to be problematic.

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- **VIF >= 5:** High multicollinearity. The correlation among predictor variables is substantial, and it may affect the reliability of the regression coefficients.

Random Forest Classification

One of the most effective ensemble learning methods, random forests classifier (RFC), has shown to be a very effective and well-liked method in pattern recognition and machine learning for high-dimensional classification and skewed issues (Breiman, 2001). A voting mechanism is used in ensemble classification techniques (Remlinger, 2007) to combine the output from several classifiers. Using bagging unpruned decision tree learners and randomly choosing features at each split, the Random Forest methodology is a learning ensemble classification strategy. For feature selection, the Random Forest method can also be utilized on its own.

The Random Forest classifier grows a large number of classification trees. A bootstrapped sample of training data is used to train each tree, and only splits at each node are searched for by random selection of a subset of the variables. The generic technique called "bootstrapping" evaluates a classifier to improve its performance and learns the training data set repeatedly. In random forests, each tree in the forest receives an input vector as input in order to be categorized. Every tree is said to vote for the class to which it belongs. Throughout the categorization process, the forest chooses the class with the most votes.

Construction of Random Forest (RF) Classifier

Since the RF classifier is an assemblage of distinct decision tree classifiers, it can increase classification accuracy. Every tree in our system is

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built using a distinct bootstrap sample from the training dataset. Each individual tree casts a vote for a single class for each observation, and the class with the majority of votes is classified by the RF classifier.

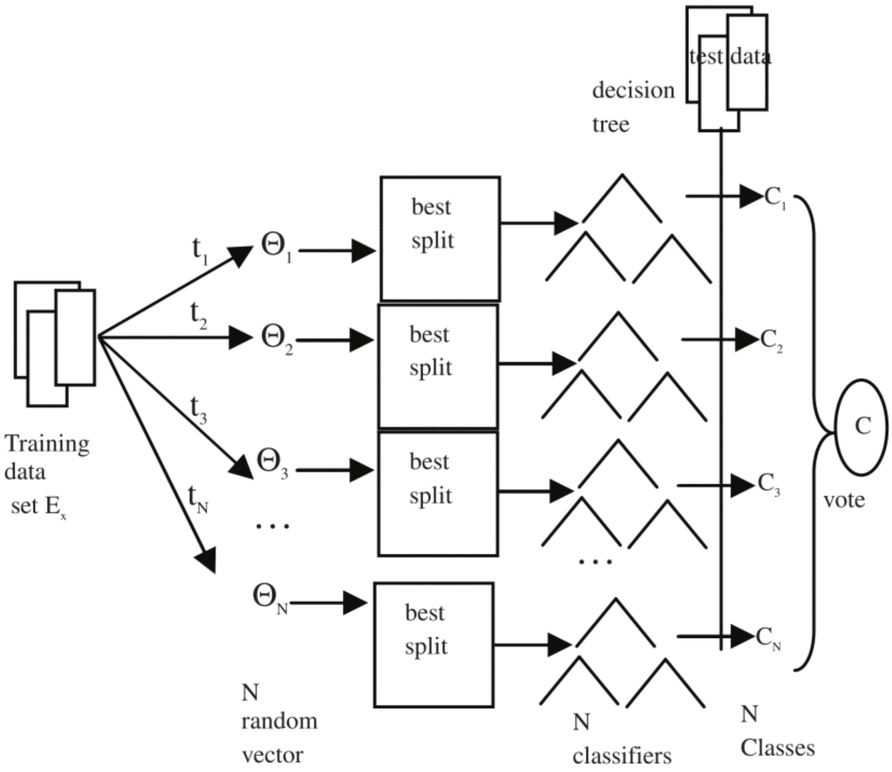

Figure 3: General Architecture of Random Forest Classification

Source: Content by Li Mingtao (August 2019)

Let $D_x = \{t_1 t_2, \dots t_N\}$ be the web pages' training data set, which includes N training instances. The training data set D_x is first bootstrapped by the RF classifier. It becomes the new training set $E_x = \{t_1 t_2, t_{3,} \dots t_N\}$ after obtaining the bootstrap. Assume the attributes list is included in $t_i = \{attr_1, attr_2, \dots attr_M\}$. There are M qualities present in every training instance t_i. The RF classifier randomly chooses the characteristics m_{try} from the training example in order to build the decision trees. In the training situation, the number of attributes (m_{try}) is always fewer than the number of attributes M. The random forest's fundamental idea is that m_{try} = $\sqrt{M}$. The RF

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classifier selects the crucial features from the set of m_{try} attributes in order to build decision trees.

Gini Index

The Gini Index, which is represented as follows, is used to choose the crucial characteristics for the optimal split of the tree:

$$gini(attr) = 1 - \sum [P_j]^2$$

$$gini_{split} = \sum_{attr=1}^{m_{try}} \frac{n_{attr}}{n} gini(attr)$$

where, P_j stands for the attribute's relative frequency $(attr)$ in class j, n_{attr} for the number of training records that were chosen at random, m_{try} for the number of attributes, and n for the total number of training records. The property with the lowest $gini_{split}$ value is the root node of the tree. Each attribute's $gini_{split}$value is used to build decision trees, with the minimum $gini_{split}$ value designating the most important attribute. The trees that were assembled at random are mature and have not been trimmed. To determine which class is the most popular, the Random Forest (RF) classifier uses a vote method. The quantity of decision trees in this system is limited to the quantity of training instances. An ensemble of these trees makes up the RF classifier. Each tree produces a single class as an output. The most popular class, which is subsequently designated as the class of maternal mortality, is chosen by vote to make the final forecast.

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Extreme Gradient Boosting

The extreme gradient boosting algorithm (XGBoost) was initially introduced by Tianqi Chen and Carlos Guestrin (Chen and Guestrin, 2016). Through the combination of many poor learners, this machine learning technique enhances learning. High flexibility and scalability are two advantages of the XGBoost technique (Yang et al., 2021b; Zhang et al., 2021b).

Since most boosting tree models only use first-order derivative information when training nth trees and are affected by the residuals of the first n-1 trees, they struggle to perform distributed training. The XGBoost model is unique. It employs a number of strategies to minimize overfitting and conducts a second-order Taylor expansion of the loss function. XGBoost may also exploit the CPU's multithreaded parallel computation to increase the running speed. This feature is a significant benefit of XGBoost over other approaches. In terms of effect and performance, XGBoost has greatly improved.

The XGBoost algorithm is defined as follows:

$$\hat{y}_i = \sum_{m=1}^{M} f_m(x_i), f_m \epsilon F$$

where F stands for the fundamental tree model and M is the total number of trees.

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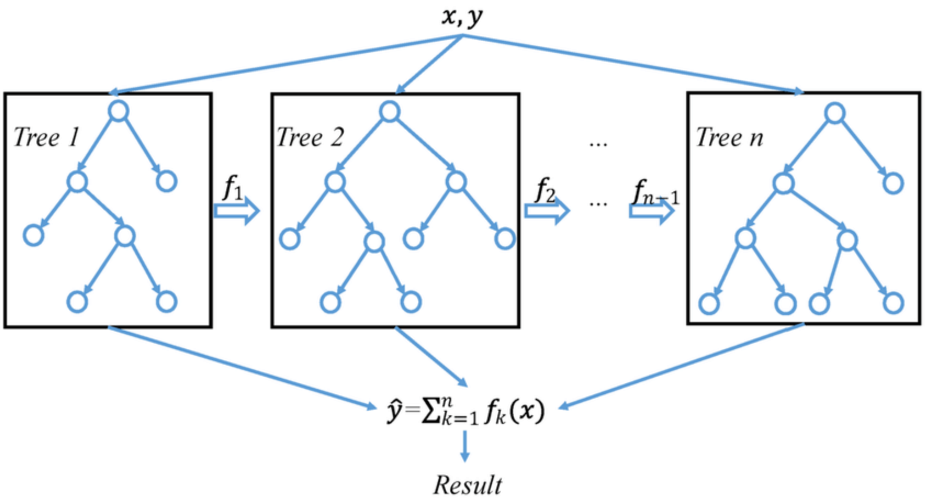

Figure 4: The general architecture for Extreme Gradient Boosting

Source: Content by Li Mingtao (August 2019)

The definition of the objective function is as follows:

$$L = \sum_{i} l(\hat{y}_i\,, y_i) + \sum_{m} \Omega(f_m)$$

The loss function l represents the error between the predicted and true values, and the regularized function Ω, which prevents overfitting, is defined as follows:

$$\boldsymbol{\Omega}(f) = \boldsymbol{\gamma T} + \frac{1}{2}\lambda\|\omega\|^2$$

where ω and T stand for the weight and leaf count of each tree, respectively.

The information gain produced following each split of the goal function may be stated as follows once the quadratic Taylor expansion on the objective function has been completed:

$$Gain = \frac{1}{2}\left[\frac{\left(\sum_{i\epsilon I_L} g_i\right)^2}{\sum_{i\epsilon I_L} h_i + \lambda} + \frac{\left(\sum_{i\epsilon I_R} g_i\right)^2}{\sum_{i\epsilon I_R} h_i + \lambda} + \frac{\left(\sum_{i\epsilon I} g_i\right)^2}{\sum_{i\epsilon I} h_i + \lambda}\right] - \gamma$$

Extreme Gradient Boosting also has the following two features:

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- To stop the model from learning unique training data, splitting ends when the threshold is larger than the weight of every sample on the leaf node.
- Each tree is built using a random sampling of the characteristics.

During the experiment, these characteristics can stop the XGBoost model from overfitting.

Measure of Performance

Performance indices such as sensitivity, specificity, accuracy, precision, and F-Measure were used to assess the performance of the classification techniques, which are RFC and XGBoost. The following are a few of the principal formulations:

Accuracy Score/Percentage

One of the most important metrics for evaluating a classification algorithm's performance is accuracy. In proportion to the total number of occurrences in the dataset, it computes the fraction of properly classified cases. To put it another way, accuracy gauges how well the algorithm's predictions correspond with the actual outcomes. A high accuracy value means that the approach performs well in terms of class distinction within the dataset. The formula to calculate it is as follows:

$$\textbf{Accuracy} = \frac{\boldsymbol{Number\ of\ Correctly\ Classified\ Instances(TP + TN)}}{\boldsymbol{Total\ Number\ of\ Instances(TP + FP + FN + TN)}}$$

True Positive Rate (Sensitivity Score)

In classification algorithms, sensitivity, also known as TPR, or True Positive Rate or recall, is an important statistic. It assesses a model's ability to properly identify positive cases among all real positive examples in a dataset. Sensitivity is especially critical in situations where the cost of false negatives

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(missed positives) is substantial, such as medical diagnosis or fraud detection. The following formula is used to calculate sensitivity:

$$\boldsymbol{Sensitivity(TPR)} = \frac{\boldsymbol{True\ Positve(TP)}}{\boldsymbol{True\ Positive(TP) + False\ Negative(FN)}}$$

Simply put, sensitivity is the percentage of real positive events properly detected by the model. A high sensitivity score suggests that the algorithm is excellent at collecting the majority of positive situations while avoiding false negatives. However, great sensitivity may come at the expense of higher false positives, therefore it's critical to find a balance depending on the application's unique requirements.

True Negative Rate (Specificity)

Specificity, commonly known as True Negative Rate (TNR), is an important measure in classification systems. While sensitivity focuses on the capacity to properly identify positive examples, specificity assesses the ability to accurately identify negative instances out of all genuine negative occurrences in the dataset. Specificity is especially critical in situations where the cost of false positives (misclassifying negative instances as positive) is considerable, such as airport security or quality control systems. Specificity is computed using the following formula:

$$\boldsymbol{Specificity(TNR)} = \frac{\boldsymbol{True\ Negative(TN)}}{\boldsymbol{True\ Negative(TN) + False\ Positive(FP)}}$$

In simple terms, specificity shows us how many genuine negative cases the model properly detected. A high specificity number suggests that the algorithm is good at differentiating between real negatives and false positives. In circumstances where misclassifying negative occurrences as positive might

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have serious repercussions, such as in security screenings or industrial processes, a high specificity is desirable.

Receiver Operating Character (ROC) and Area Under the Curve (AUC)

It is common practice to evaluate a diagnostic test's efficacy using receiver operating characteristic (ROC) curves (Kerekes, 2008). There is a wealth of information in this technique to help comprehend and enhance classifier performance. The true positive rate vs the false positive rate is plotted on the ROC curve. Theoretically, a classifier that performs better would have a ROC curve that huggees the upper left corner of the graph, indicating a higher True Positive Rate and a lower False Positive Rate. To determine a classification model's overall performance, one uses the area under the ROC curve. AUC is a metric that measures overall performance and has values between 0 and 1, with the following values explained:

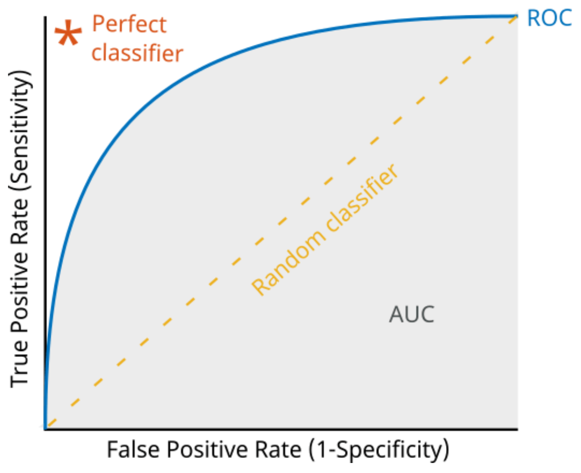

Figure 5: Illustration of the ROC and the AUC

Source: *The website of MathWorks (https://www.mathworks.com)*

A higher AUC value implies that the model can distinguish more clearly between positive and negative classifications. It offers a single, simple metric for comparing and choosing models. AUC is especially beneficial when

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the classes are unbalanced since it is less impacted by class distribution than accuracy.

Positive Predictive Rate (Precision Score)

The proportion of positive test results that are real positives, or accurate diagnoses, is called precision, often referred to as positive predictive value. This is a crucial performance indicator for diagnostic methods since it shows the probability that a positive test will really reveal the underlying condition that is being checked for.

$$Precision(PPR) = \frac{TP}{TP + FP} \times 100\%$$

Confusion Matrix

An essential instrument for assessing categorization schemes is a confusion matrix. It shows the actual and projected class labels for a dataset to offer a clear and complete assessment of the model's performance. The matrix is especially effective for binary classification issues with two classes: positive and negative.

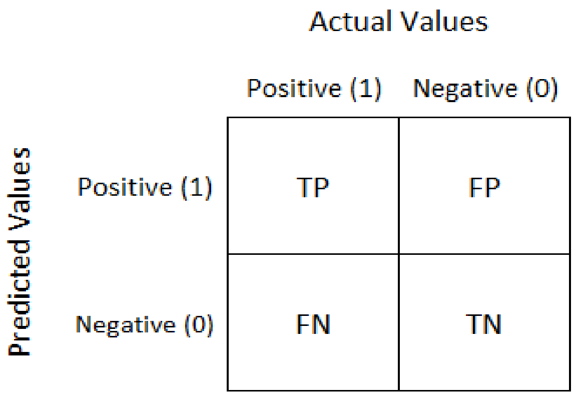

Figure 6: An illustration of Confusion Matrix with the actual and predicted values

Source: *Scientific Figure on ResearchGate. Available from: https://www.researchgate.net [accessed 7 May, 2024]*

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The confusion matrix's diagonal values (True Positives and True Negatives) should be much greater than the off-diagonal values (False Positives and False Negatives). High diagonal values imply that the model classifies examples properly.

Cross Validation

Cross-validation is an important approach in machine learning, particularly for testing the effectiveness and generalizability of classification systems. It comprises folding or separating the dataset into many subgroups. A portion of the data (the training set) is used to train the algorithm, and the remaining data (the validation or test set) is used to verify it. To provide a more reliable evaluation of the model's performance, this process is repeated many times using distinct subsets for training and validation. The average of the findings is then utilized. Many machine learning challenges are addressed by cross-validation, including overfitting (the situation in which a model performs well on training data but is unable to generalize to new, unknown data) and the impact of the initial random split of the data. In this study, the KFold, Stratified KFold, and Leave One Out cross validation were used to access the efficiency and generalization of the classification systems used.

The Advantages, Disadvantages and Importance of the three models

Each of these models has unique advantages and disadvantages, making them suitable for different types of research problems. Logistic regression is valued for its simplicity and interpretability, making it a good starting point for analysis. Random forest classification offers robustness and the ability to model complex relationships, making it a powerful tool for varied datasets. XGBoost stands out for its high performance and scalability,

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making it ideal for large and complex datasets. Together, these models provide a comprehensive toolkit for tackling diverse research questions in classification tasks.

Chapter Summary

In conclusion, this chapter serves as a thorough guide to research technique, giving a clear and rationale-driven explanation of the selected study design, sampling strategy, data collection, and analytic methodologies. This chapter not only confirms the rigor and validity of the research but also permits future researchers in the field to replicate the study.

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CHAPTER FOUR

RESULTS AND DISCUSSION

Introduction

This chapter summarizes the study's findings and gives a discussion of those findings. This study investigated three alternative modeling strategies. The findings of the logistic regression study were compared to the results of the random forest and extreme gradient-boosting data mining approaches. The data mining program (software) Python was used to develop the models, while with data management, the software STATA was employed. Exploratory analysis, logistic regression, random forest, extreme gradient boosting, and method comparison are the chapters' five sections.

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Preliminary Analysis of Data

Table 1: Descriptive statistics on the demographic and socioeconomic variables of the deceased women

	Frequency	Percent
Region (n = 1240)		
Western	111	9.0%
Central	109	8.8%
Greater Accra	111	9.0%
Volta	126	10.2%
Eastern	152	12.3%
Ashanti	100	8.1%
Brong Ahafo	114	9.2%
Northern	227	18.3%
Upper east	99	8.0%
Upper West	91	7.3%
Residence (n = 1240)		
Urban	589	47.5%
Rural	651	52.5%
Religion (n = 1240)		
No Religion	96	7.7%
Christian	843	68.0%
Islam	253	20.4%
Traditional/spiritualist	48	3.9%
Age at Death (n =1240)		
0 to 19	129	10.4%
20 to 29	289	23.3%
30 to 39	433	34.9%
40 to 49	389	31.4%
Occupation (n = 1240)		
Professional and Administrative Occupation	38	4.6%
Skilled and Unskilled Labor	349	42.1%
Sales and Service Workers	441	53.3%
Education Status (n = 1240)		
Never Attended School	384	31.0%
Primary or Basic	690	55.6%
Secondary and Tertiary	166	13.4%
Marital Status (n = 1240)		
Single	311	25.1%
Married/Cohabitation	739	59.6%
Separated/Divorced/Widowed	190	15.3%

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According to Table 1, the sample comprised 1,240 participants from various regions of Ghana. The distribution across regions is as follows: Western (n = 111, 9.0%), Central (n = 109, 8.8%), Greater Accra (n = 111, 9.0%), Volta (n = 126, 10.2%), Eastern (n = 152, 12.3%), Ashanti (n = 100, 8.1%), Brong Ahafo (n = 114, 9.2%), Northern (n = 227, 18.3%), Upper East (n = 99, 8.0%), and Upper West (n = 91, 7.3%). The Northern region had the highest representation in the sample (18.3%), followed by the Eastern (12.3%) and Volta (10.2%) regions. This distribution might reflect the varying population sizes and maternal mortality rates across different regions.

The deceased places of residence were nearly evenly split between urban and rural areas. Specifically, 589 of the deceased pregnant women (47.5%) resided in urban areas, while 651 of them (52.5%) lived in rural areas. The religious affiliations were as follows: No Religion (n = 96, 7.7%), Christian (n = 843, 68.0%), Islam (n = 253, 20.4%), and Traditional/Spiritualist (n = 48, 3.9%). Also, their ages at death were categorized as follows: 0 to 19 years (n = 129, 10.4%), 20 to 29 years (n = 289, 23.3%), 30 to 39 years (n = 433, 34.9%), and 40 to 49 years (n = 389, 31.4%). The results indicate that the majority of maternal deaths occurred in the age groups 30 to 39 years (34.9%) and 20 to 29 years (23.3%). This suggests that interventions should focus on women in their prime reproductive years to effectively reduce maternal mortality rates.

The occupational distribution of the deceased women was as follows: Professional and Administrative Occupation (n = 38, 4.6%), Skilled and Unskilled Labor (n = 349, 42.1%), and Sales and Service Workers (n = 441, 53.3%). Most participants were engaged in skilled and unskilled labor (42.1%)

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and sales and service work (53.3%). These occupations may have implications for maternal health, particularly regarding access to healthcare services and the ability to afford care.

Their educational status was captured as follows: never attended school (n = 384, 31.0%), primary or basic education (n = 690, 55.6%), and secondary and tertiary education (n = 166, 13.4%). Also, the marital statuses were categorized as follows: single (n = 311, 25.1%), married/cohabitation (n = 739, 59.6%), and separated/divorced/Widowed (n = 190, 15.3%). A significant portion of the participants had only primary or basic education (55.6%), with 31.0% never having attended school. Education is a crucial determinant of health outcomes, and these findings underscore the importance of improving educational opportunities for women as a strategy to reduce maternal mortality.

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Table 2: Some mental health and illness characteristics of deceased women

	Frequency	Percent
Dementia (n = 1240)		
No	1,211	97.7%
Yes	29	2.3%
Depression (n = 1240)		
No	1,180	95.2%
Yes	60	4.8%
Mental Disorder (n = 1240)		
No	1,212	97.7%
Yes	28	2.3%
Cancer (n = 1240)		
No	1,187	95.7%
Yes	53	4.3%
Fever (n = 1240)		
No	673	52.3%
Yes	567	45.7%
Sickle Cell (n = 1240)		
No	1,214	97.9%
Yes	26	2.1%
HIV test (n = 1240)		
No	1080	87.1%
Yes	160	12.9%
Malaria test (n = 1240)	N	
No	927	74.8%
Yes	313	25.2%
Blood Pressure (n = 1240)		
No	1,066	86.0%
Yes	174	14.0%

From Table 2, the vast majority of the deceased women did not have cancer (n = 1,187, 95.7%), while a small percentage had malignancies (n = 53, 4.3%). The low prevalence of cancer (4.3%) among the deceased women indicates that cancer may not be a primary contributing factor to maternal mortality in these results. However, it remains essential to monitor cancer as a potential risk factor. Just over half of the deceased women did not have a fever at the time of death (n = 673, 52.3%), whereas a substantial proportion had a

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fever (n = 567, 45.7%). The high incidence of fever (45.7%) among the deceased women suggests that infectious diseases might play a substantial role in maternal mortality. Fever can be a symptom of various infections, including malaria and other febrile illnesses, which are prevalent in many parts of Ghana.

The overwhelming majority of the deceased women did not have sickle cell disease (n = 1,214, 97.9%), with a very small percentage affected by it (n = 26, 2.1%). Most of the deceased women had been tested for HIV and reported being negative for the virus (n = 1,080, 87.1%), while a smaller percentage had tested positive for HIV (n = 160, 12.9%). A significant majority of the deceased women had been tested negative for malaria as well (n = 927, 74.8%), whereas a quarter had been tested positive for malaria (n = 313, 25.2%). Malaria is a known cause of severe complications during pregnancy and is prevalent in many regions of Ghana.

From the dataset, a larger portion of the sample did not have dementia, depression, and other mental disorders; these may, therefore, not be major risk factors in the predictive model for maternal mortality in Ghana. Only 2.3% of the sample had dementia, 4.8% had depression, and 2.3% had other mental disorders. These low percentages are indicative that, while there are cases of mental health conditions in the studied population, they are quite rare. The prevalence could indicate a limited immediate impact on maternal mortality in this context, though monitoring is still continuously important, given the indirect effects of mental health on general health.

Most of the deceased women did not have high blood pressure (n = 1,066, 86.0%), while a smaller percentage had high blood pressure (n = 174,

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14.0%). High blood pressure was present in 14.0% of the deceased women. Hypertension and related conditions, such as preeclampsia and eclampsia, are significant risk factors for maternal mortality.

Table 3: Health and illness characteristics of deceased women

	Frequency	Percent
Place of Death (n = 1240)		
Home Death	528	42.6%
Health Facility	599	48.3%
Other	113	9.1%
Time to Nearest Hospital (n = 1240)		
Below 120mins	1,194	96.3%
120 to 240	13	1.0%
Above 240	33	2.7%
Receive Treatment (n = 1240)		
No	181	14.6%
Yes	1,059	85.4%
Intake Alcohol (n = 1240)		
No	1,025	82.7%
Yes	215	17.3%
Used Tobacco (n = 1240)		
No	1,224	98.7%
Yes	16	1.3%
Traditional Medication (n = 1240)		
No	780	62.9%
Yes	460	37.1%
Traveled to Hospital (n = 1240)		
No	399	32.2%
Yes	841	67.8%
Season of Dead (n = 1240)		
Dry Season	669	54.0%
Wet Season	571	46.0%

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From Table 3, the majority of the deceased women died in a health facility (n = 599, 48.3%), followed closely by those who died at home (n = 528, 42.6%). A smaller percentage died in other locations (n = 113, 9.1%). Most of the deceased women were within 120 minutes of the nearest hospital (n = 1,194, 96.3%). A small percentage were 120 to 240 minutes away (n = 13, 1.0%), and a slightly larger percentage were more than 240 minutes away (n = 33, 2.7%).

Also, according to the results, most of the deceased women received treatment (n = 1,059, or 85.4%), whereas a smaller percentage did not receive treatment (n = 181, or 14.6%). A significant majority of the deceased women did not consume alcohol (n = 1,025, 82.7%), while a smaller percentage did consume alcohol (n = 215, 17.3%). The overwhelming majority of the deceased women did not use tobacco (n = 1,224, 98.7%), with a very small percentage having used tobacco (n = 16, 1.3%).

A notable proportion of the deceased women used traditional medication (n = 460, 37.1%), whereas the majority did not use traditional medication (n = 780, 62.9%). A substantial number of the deceased women traveled to the hospital (n = 841, 67.8%), while a smaller percentage did not travel to the hospital (n = 399, 32.2%). Slightly more of the deceased women died during the dry season (n = 669, 54.0%) compared to those who died during the wet season (n = 571, 46.0%).

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Table 4: Continuation of other health and illness characteristics of deceased women

	Frequency	Percent
Transport Means (n = 833)		
Public Transport	550	66.0%
Private Car	79	9.5%
Motorcycle/Bicycle/Canoe/Boat/Ferry	139	16.7%
Ambulance	39	4.7%
On Foot	26	3.1%
Place she gave birth (n = 125)		
Public Health Facility	96	76.8%
Private Health Facility	5	4.0%
Non-Health Facility/Home Delivery	24	19.2%
Professional assistance (n = 125)		
No	21	16.8%
Yes	104	83.2%
Abortion Attempt (n = 254)		
No	246	96.9%
Yes	8	3.1%
Previous Caesarean Session (n= 192)		
No	171	89.1%
Yes	21	10.9%
Bleeding Pregnant (n = 254)		
No	236	92.9%
Yes	18	7.1%
Pregnancy Miscarried (n = 254)		
No	230	90.6%
Yes	24	9.4%
Maternal Mortality (n = 1240)		
No	1,076	86.8%
Yes	164	13.2%

From Table 4, among the deceased women, the most common means of transport to a health facility was public transport (n = 550, 66.0%). Other means included motorcycle/bicycle/canoe/boat/ferry (n = 139, 16.7%), private car (n = 79, 9.5%), ambulance (n = 39, 4.7%), and on foot (n = 26, 3.1%). Of the women who had given birth, the majority delivered in public health facilities (n = 96, 76.8%), followed by non-health facilities or home deliveries

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(n = 24, 19.2%). A small number delivered in private health facilities (n = 5, 4.0%).

A significant majority of the women received professional assistance during birth (n = 104, 83.2%), while a smaller percentage did not receive professional assistance (n = 21, 16.8%). Among the women, a very small percentage attempted abortion (n = 8, 3.1%), while the vast majority did not attempt abortion (n = 246, 96.9%). The majority of the women had not undergone a previous Caesarean section (n = 171, 89.1%), while a smaller percentage had (n = 21, 10.9%). Most of the women did not experience bleeding during pregnancy (n = 236, 92.9%), whereas a smaller percentage did (n = 18, 7.1%). The majority of the women did not experience a miscarriage (n = 230, 90.6%), while a smaller percentage did (n = 24, 9.4%). Out of the total sample, a smaller proportion of the women experienced maternal mortality (n = 164, 13.2%), while the majority did not (n = 1,076, 86.8%).

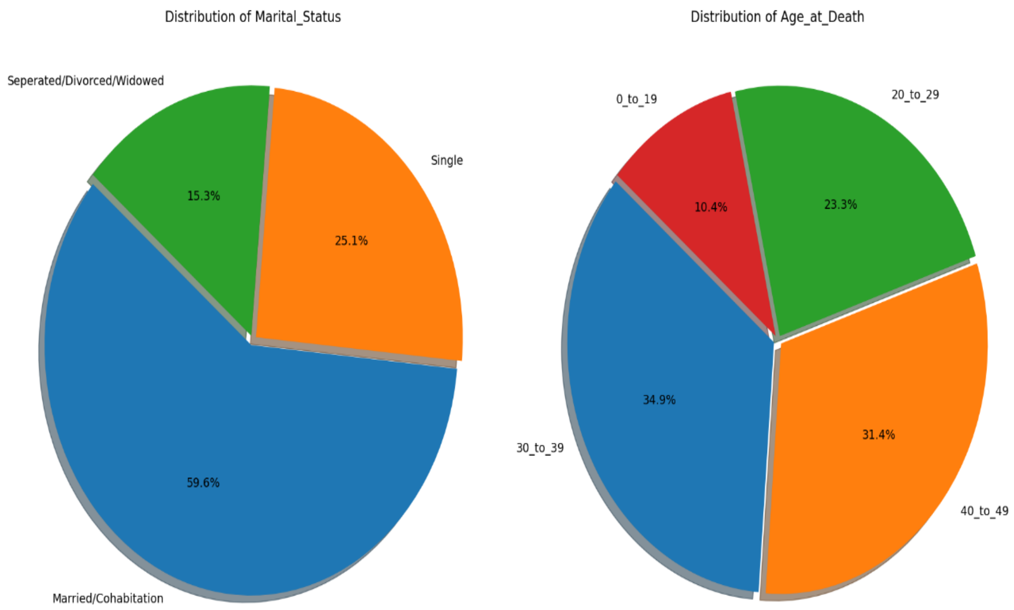

Figure 7: A pie chart distribution of the marital status and age at death of the deceased women.

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Figure 7 presents pie charts illustrating the distribution of marital status and age at death among the deceased women in the sample. The largest proportion of deaths occurred in the age group of 30 to 39 years (34.9%), followed closely by the 40 to 49 years group (31.4%). The 20 to 29-year-old group accounts for 23.3% of the deaths, while the smallest proportion of deaths occurred in the 0 to 19-year-old group (10.4%). This distribution suggests that the majority of deaths are concentrated in the 30 to 49-year-old age range, indicating a critical period for health interventions.

The majority of the deceased women were married or in cohabitation (59.6%), indicating that more than half of the sample was in a committed relationship at the time of death. A significant portion of the women were single (25.1%), while a smaller segment was separated, divorced, or widowed (15.3%). This distribution highlights the prevalence of marital relationships among the deceased women, which could be an important factor in understanding their social and economic contexts.

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Table 5: Performing the Variance Inflation Factor for Multicollinearity

Features	Variance Inflation Factor (VIF)
Time to Nearest Hospital	1.02
Place of Death	1.14
Marital Status	1.39
Education Status	1.20
Blood Pressure	1.07
Receive Treatment	1.08
Cancer	1.04
Sickle Cell	1.03
Traditional Medication	1.10
HIV Test	1.11
Malaria Test	1.23
Residence	1.11
Season of Dead	1.02
Fever	1.18
Age at Death	1.43
Dementia	1.20
Depression	1.14
Mental Disorder	1.17

The assessment of multicollinearity among the predictor variables was conducted using the Variance Inflation Factor (VIF). The VIF values for each variable are reported in Table 5. Typically, a VIF value greater than 10 suggests significant multicollinearity, which can inflate the variance of coefficient estimates and affect the stability of the regression model (Kutner, Nachtsheim, & Neter, 2004). The VIF values for all the predictors are below the threshold of 10, indicating that multicollinearity is not a significant concern in this dataset. Specifically, the VIF values for all variables range from 1.02 to 1.43, suggesting low to negligible multicollinearity among the predictors. These results imply that the predictor variables do not exhibit strong linear relationships with one another, ensuring the stability and reliability of the regression model coefficients (Tabachnick & Fidell, 2013). Therefore, the multicollinearity is within acceptable limits, allowing for

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meaningful interpretation of the regression coefficients in the subsequent analysis.

Research Objective One

To identify the most critical medical and mental health factors contributing to maternal mortality in Ghana.

Table 6: A logistics regression analysis to find out which risk variable(s) are most crucial for predicting maternal death in Ghana

	Adjusted Odds Ratio	**AME (dydx)**	**p-value**
Intercept	0.041 (-4.237 -2.138)		0.000 ***
Time to Nearest Hospital			
Below 120 mins	(Ref)		
120 to 240 mins	1.262 (-1.540 2.006)	0.022	0.797
Above 240 mins	1.170(-0.876 1.191)	0.015	0.766
Place of Death			
Home Death	(Ref)		
Health Facility	5.146 (1.110 2.166)	0.153	0.000 ***
Other	3.541 (0.554 1.975)	0.118	0.000 ***
Marital Status			
Single	(Ref)		
Married/Cohabitation	5.481 (1.060 2.342)	0.159	0.000 ***
Separated/Divorced/Widow	1.175 (-0.894 1.217)	0.015	0.764
Education Status			
Never Attended School	(Ref)		
Primary or Basic	0.886 (-0.562 0.319)	-0.011	0.590
Secondary and Tertiary	0.745 (-0.932 0.343)	-0.028	0.366
Blood Pressure			
No	(Ref)		
Yes	0.532 (-1.233 -0.029)	-0.059	0.040 *
Cancer			
No	(Ref)		
Yes	0.548 (-1.832 0.630)	-0.056	0.339
Traditional Medication			
No	(Ref)		
Yes	0.467 (-1.244 -0.277)	-0.071	0.002 **
Received Treatment			
No	(Ref)		
Yes	0.924 (-0.643 0.485)	-0.073	0.784
HIV Test			

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No	(Ref)		
Yes	1.277 (-0.362 0.851)	0.023	0.429
Sickle Cell			
No	(Ref)		
Yes	1.255 (-1.096 1.549)	0.021	0.737
Malaria Test			
No	(Ref)		
Yes	0.738 (-0.829 0.221)	-0.028	0.257
Residence			
Urban	(Ref)		
Rural	1.322 (-0.108 0.667)	0.026	0.158
Season Dead			
No	(Ref)		
Yes	0.661 (-0.792 -0.036)	-0.039	0.032 *
Fever			
No	(Ref)		
Yes	0.613 (-0.907 -0.072)	-0.046	0.022 *
Depression			
No	(Ref)		
Yes	0.779 (-1.286 0.786)	-0.023	0.636
Mental Disorder			
No	(Ref)		
Yes	0.258 (-3.530 0.821)	-0.127	0.222
Age at Death			
0_to_19	(Ref)		
20_to_29	1.181 (-0.662 0.994)	0.016	0.695
30_to_39	0.827 (-1.035 0.655)	-0.018	0.660
40_to_49	0.291 (-2.171 -0.299)	-0.115	0.010 **

A logistic regression analysis was conducted to identify the most critical medical and mental health factors contributing to maternal mortality in Ghana. The analysis focused on a variety of variables to assess their significance and impact. The results, including adjusted odds ratios (AOR), average marginal effects (AME), and p-values for each predictor, are presented in Table 6. The intercept of the model was significant (AOR = 0.041, 95% CI [-4.237, -2.138], $p < 0.001$), indicating a baseline likelihood of maternal death when all other variables are held constant.

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Maternal deaths were significantly more likely to occur in health facilities compared to home deaths (AOR = 5.146, 95% CI [1.110, 2.166], AME = 0.153, p = 0.000). This suggests that women who die in health facilities are over five times more likely to experience maternal death compared to those who die at home. Deaths occurring in other places also had significantly higher odds compared to home deaths (AOR = 3.541, 95% CI [0.554, 1.975], AME = 0.119, p = 0.000). Married or cohabitating women had significantly higher odds of maternal death compared to single women (AOR = 5.481, 95% CI [1.060, 2.342], AME = 0.159, p = 0.000), indicating that married or cohabitating women are more than five times more likely to die from maternal causes compared to single women.

High blood pressure was associated with lower odds of maternal death (AOR = 0.532, 95% CI [-1.233, -0.029], AME = -0.059, p = 0.040). Use of traditional medication was significantly associated with lower odds of maternal death (AOR = 0.467, 95% CI [-1.244, -0.277], AME = -0.071, p = 0.002). Women who used traditional medication were about 53% less likely to die from maternal causes. Deaths occurring in the wet season had significantly lower odds compared to those in the dry season (AOR = 0.661, 95% CI [-0.792, -0.036], AME = -0.039, p = 0.032). Women who are pregnant and mostly due for delivery in the wet season were about 35% less likely to die from maternal causes.

Having a fever was associated with significantly lower odds of maternal death (AOR = 0.613, 95% CI [-0.907, -0.072], AME = -0.046, p = 0.022). Women aged 40 to 49 years had significantly lower odds of maternal death compared to those aged 0 to 19 years (AOR = 0.291, 95% CI [-2.171, -

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0.299], AME = -0.115, p = 0.010). This indicates that older women, particularly those aged 40 to 49, may have better health management or access to resources compared to younger women.

Place of Death and Maternal Mortality: A Call for Improved Healthcare Facilities

The finding that maternal deaths are significantly more likely to occur in health facilities compared to home deaths highlights a critical area of concern within maternal healthcare in Ghana. This disparity suggests that many women present at healthcare facilities with severe obstetric complications that may have been preventable or manageable with timely intervention. The high rate of maternal deaths in these settings may indicate inadequate emergency obstetric services, insufficient resources, or delays in seeking care. Health facilities must be adequately equipped to handle high-risk pregnancies, which includes access to trained healthcare professionals, emergency supplies, and the ability to provide comprehensive obstetric care.

Additionally, the perception of health facilities as safe places for childbirth must be reinforced in communities to encourage timely healthcare-seeking behaviors. There is a need for continuous training and support for healthcare providers to enhance their skills in emergency obstetric care. Initiatives that promote community awareness of the dangers of pregnancy complications and the importance of timely hospital visits could also help mitigate this issue. Ultimately, improving the quality of care in health facilities can significantly reduce maternal mortality rates, as many women may have severe conditions that require immediate intervention (WHO, 2019).

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Marital Status and Maternal Mortality

The significantly higher odds of maternal death among married or cohabitating women suggest a complex interplay between marital dynamics and maternal health outcomes. Socio-cultural factors often influence healthcare-seeking behavior among married women, potentially leading to delayed access to necessary medical services. In many communities, women may prioritize family needs over their health, or they may face pressure from partners or family to avoid seeking professional medical help until complications become severe (Koblinsky et al., 2006).

Addressing these socio-cultural barriers is vital in reducing maternal mortality. Community-based health education programs that engage men as partners in maternal health can help shift perspectives on reproductive health and the importance of maternal care. Moreover, these programs should emphasize the significance of supportive environments where women feel empowered to prioritize their health and seek care without stigma or fear of judgment. Increased awareness of maternal health rights and available services can help bridge the gap between marital status and health-seeking behavior, ultimately improving maternal health outcomes (Ghana Health Service, 2021).

Blood Pressure Management and its impact on Maternal Mortality

The association of lower maternal mortality with effective management of high blood pressure underscores the critical role of prenatal care in maternal health. Hypertensive disorders are a leading cause of maternal mortality worldwide, and this finding suggests that interventions focusing on early detection and management of these conditions are having a positive impact (Abalos et al., 2013). The emphasis on routine prenatal check-ups

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facilitates early identification of hypertension, allowing for timely intervention and management to prevent severe complications.

Moreover, integrating modern healthcare practices with traditional practices could enhance the management of hypertension during pregnancy. Training healthcare providers on the importance of regular monitoring and personalized treatment plans for women with a history of hypertension can improve maternal health outcomes. Continuous public health campaigns that promote awareness of the risks associated with high blood pressure during pregnancy can further encourage women to seek regular prenatal care (WHO, 2020).

Traditional Medicine's Role in reducing Maternal Mortality

The significant association between the use of traditional medication and lower maternal mortality highlights the importance of culturally appropriate healthcare solutions. Many women in Ghana rely on traditional healers and remedies for health issues, including during pregnancy. While some traditional practices may have beneficial effects, they often operate outside the formal healthcare system, leading to gaps in care (Ahmed et al., 2010).

Integrating beneficial traditional practices with formal healthcare systems can enhance maternal health outcomes. Collaboration between traditional healers and healthcare providers can foster trust and improve access to essential services for women who may otherwise avoid modern healthcare due to cultural beliefs. Training traditional healers on recognizing severe complications and referring women to formal healthcare settings can serve as a bridge, ensuring that women receive comprehensive care. Furthermore,

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awareness campaigns that educate women about the safety and efficacy of modern maternal healthcare options, alongside culturally respected traditional practices, can empower women to make informed health choices, ultimately reducing maternal mortality.

Seasonal Variations and their influence on Maternal Mortality

The finding that maternal deaths are lower in the wet season suggests that environmental factors may significantly impact maternal health outcomes. During the wet season, increased access to healthcare services, availability of medical resources, and better community awareness regarding maternal health can contribute to improved outcomes (UNICEF, 2016). Conversely, the dry season may present challenges, such as increased disease prevalence (e.g., malaria) and potential disruptions to healthcare access.

To address seasonal variations in maternal mortality, targeted interventions are essential. Preparing healthcare facilities for seasonal changes by ensuring adequate staffing, resources, and training can help maintain care quality throughout the year. Seasonal health campaigns that address specific risks associated with each season, such as promoting mosquito control measures in the dry season, can further support maternal health (World Bank, 2020). Additionally, community mobilization efforts that align with seasonal patterns can increase healthcare-seeking behaviors during critical periods, leading to better maternal health outcomes.

Infection Management and Maternal Mortality: The Case of Fever

The association between fever and lower maternal mortality may indicate effective management of infections that could otherwise escalate to life-threatening complications. This finding underscores the importance of

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timely diagnosis and treatment of infections during pregnancy. Maternal mortality can be significantly impacted by the presence of infections, which may lead to conditions such as sepsis if not managed appropriately (Abalos et al., 2013).

Enhanced healthcare protocols that focus on the early detection and treatment of infections can help mitigate maternal mortality. Training healthcare providers on recognizing signs of infection and implementing standardized care pathways can lead to more effective interventions. Public health initiatives that promote maternal awareness of infection symptoms and the importance of seeking care can further improve outcomes. Additionally, integrating maternal health education within antenatal care can empower women to recognize and respond to symptoms proactively, ultimately reducing the risk of maternal mortality related to infectious diseases.

Age and Maternal Mortality

The observation that older women (ages 40 to 49) have lower odds of maternal death compared to younger women (ages 0 to 19) suggests that older women may benefit from greater health management or access to resources. This finding aligns with existing literature indicating that older women are often more experienced in navigating healthcare systems and may have more stable access to health services (Bloom et al., 2001).

However, this also highlights a pressing need for targeted interventions for younger women, who often face higher maternal mortality risks. Young women may lack adequate knowledge about reproductive health, face barriers to accessing care, or experience socio-economic challenges that limit their healthcare options. Programs aimed at educating younger women about

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reproductive health, maternal care, and their rights within the healthcare system are essential. Moreover, engaging young men in these discussions can foster supportive environments where young women feel empowered to prioritize their health. Ensuring that healthcare systems are sensitive to the unique needs of younger women can lead to improved maternal health outcomes and reduce maternal mortality rates (UNFPA, 2019).

Social Determinants of Health (SDH) Model

The Social Determinants of Health (SDH) model posits that health outcomes are influenced by a range of socio-economic and environmental factors rather than just biological or medical ones (WHO, 2008). This comprehensive framework recognizes the multi-dimensional influences on health and well-being, including social, economic, and environmental conditions that people live in. The findings of this study on maternal mortality in Ghana align with the SDH model, highlighting the significant roles of factors such as marital status, place of death, and seasonal variations.

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Research Objective Two

To predict the probability of maternal death, based on a combination of medical, socio-economic, and mental health variables.

Logistic Regression Classification

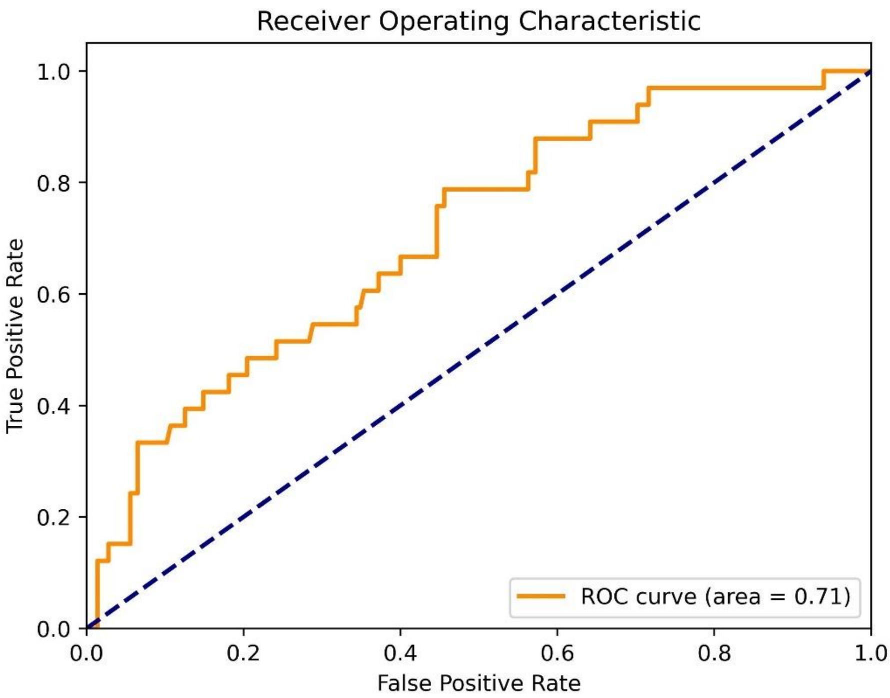

Figure 8: Receiver Operating Characteristic curve and Area Under the curve of a logistic model for predicting maternal mortality outcome

From Figure 8, the ROC curve is a graphical tool used to evaluate the diagnostic performance of a binary classifier system across various threshold settings. In this study, the Area Under the Curve (AUC) value of 0.71 indicates that the logistic regression model possesses a fair level of discriminative ability. Specifically, this AUC value suggests that the model has a 71% probability of correctly differentiating between a randomly selected instance of maternal death and a randomly selected instance of survival. This level of discrimination reflects the reasonable predictive capabilities of the logistic regression model for maternal mortality in the given dataset.

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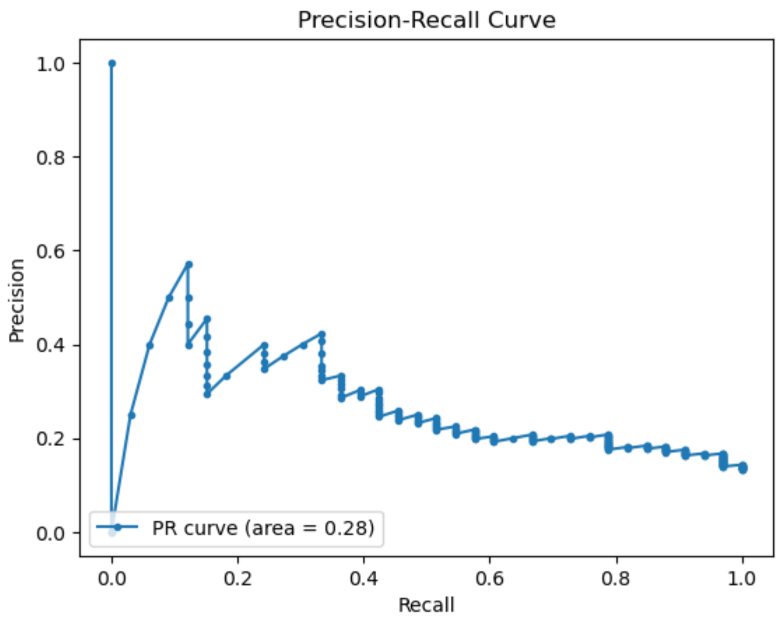

Figure 9: A precision-recall curve of the logistic model for predicting maternal mortality outcome

In this study, the precision-recall curve generated from the logistic regression model for predicting maternal mortality outcomes shows an area under the curve (AP) of 0.28. This value indicates that the model's performance in terms of balancing precision and recall is not the best. Specifically, an AP of 28% suggests that the logistic regression model struggles to achieve high precision and recall simultaneously when distinguishing between instances of maternal death and survival.

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Random Forest Classification

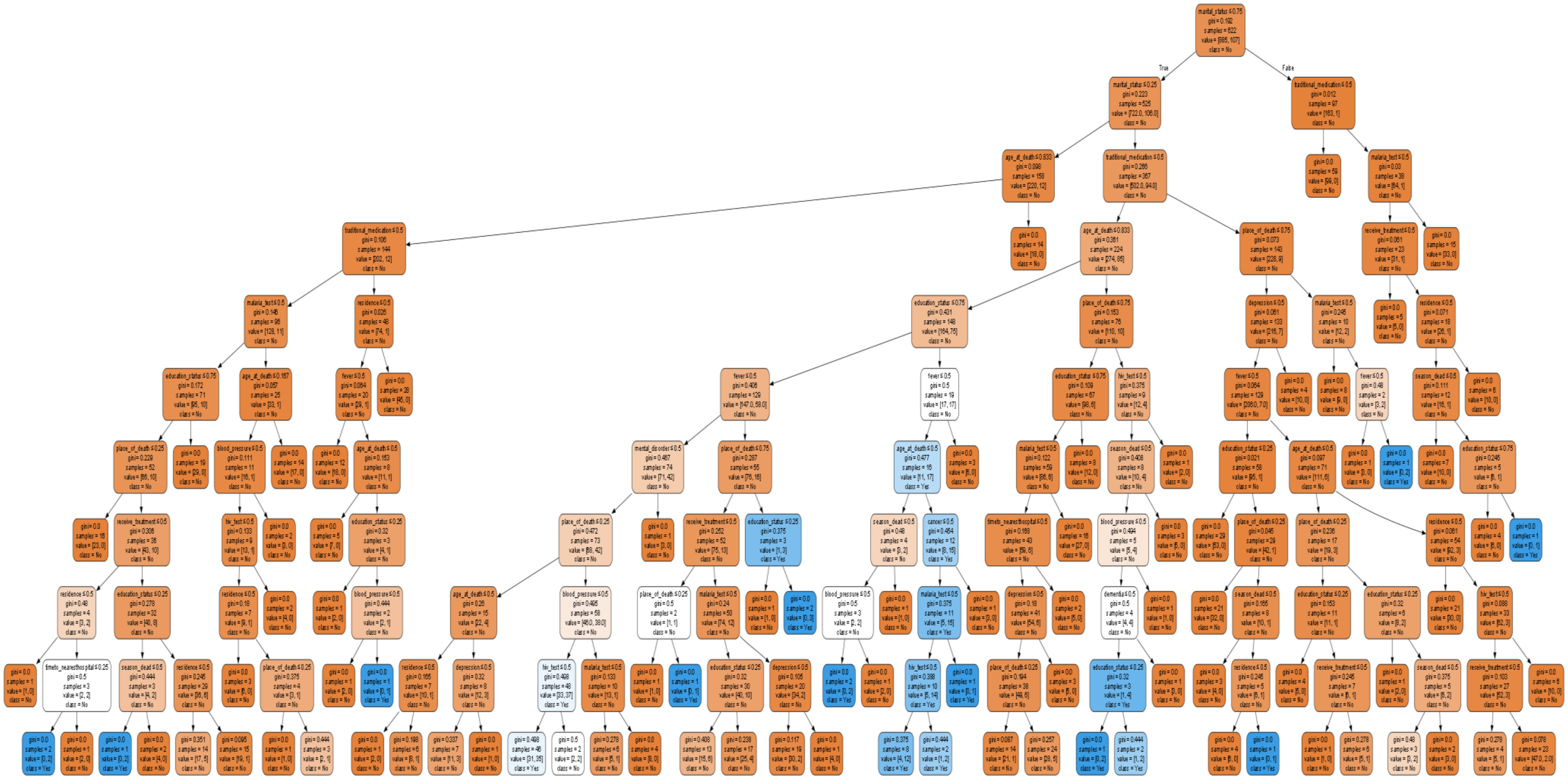

Figure 10: A Random Forest Classification analysis on the predicting of maternal mortality in Ghana.

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Figure 10 presents a Random Forest Classification analysis used to predict maternal mortality in Ghana. The visualized decision tree from the random forest ensemble highlights the key variables and decision paths leading to the prediction of maternal mortality. Below is a detailed interpretation and analysis of the significant splits and features within the tree.

The first and most significant split in the tree is based on whether the deceased had a fever (Fever ≤ 0.5). These initial splits underscore that fever is a critical factor in predicting maternal mortality. Individuals with a fever exhibit different mortality risks compared to those without. The next major split occurs based on age at death (Age at Death ≤ 0.167). This indicates that age is a significant predictor, with younger age groups (e.g., under 20 years) showing a different risk profile compared to older age groups.

This feature further divides the nodes, distinguishing between home deaths, health facility deaths, and other locations. The place of death is significant, with different mortality risks associated with each location. This split highlights the importance of healthcare accessibility and the setting in which care is received. Blood pressure (blood pressure ≤ 0.5) emerges as another critical factor. This split indicates the health status of the deceased, with high blood pressure associated with different outcomes compared to normal levels.

The use of traditional medication (Traditional Medication ≤ 0.5) impacts mortality risk. Those using traditional medicine show distinct risk profiles, suggesting variations in health outcomes based on treatment practices. The season during which the death occurred (Season Dead ≤ 0.5) influences the prediction, indicating that seasonal variations affect mortality

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outcomes. This split underscores the impact of environmental and seasonal factors on maternal health. Educational attainment (Education Status ≤ 0.25) impacts mortality, with differences seen between those with lower and higher education levels. This highlights the role of education in health outcomes and access to healthcare services. The status of malaria testing (Malaria test ≤ 0.5) and the presence of sickle cell disease (Sickle Cell ≤ 0.5) further refine the prediction, indicating additional health-related risk factors. These factors contribute to the overall health profile and associated risks.

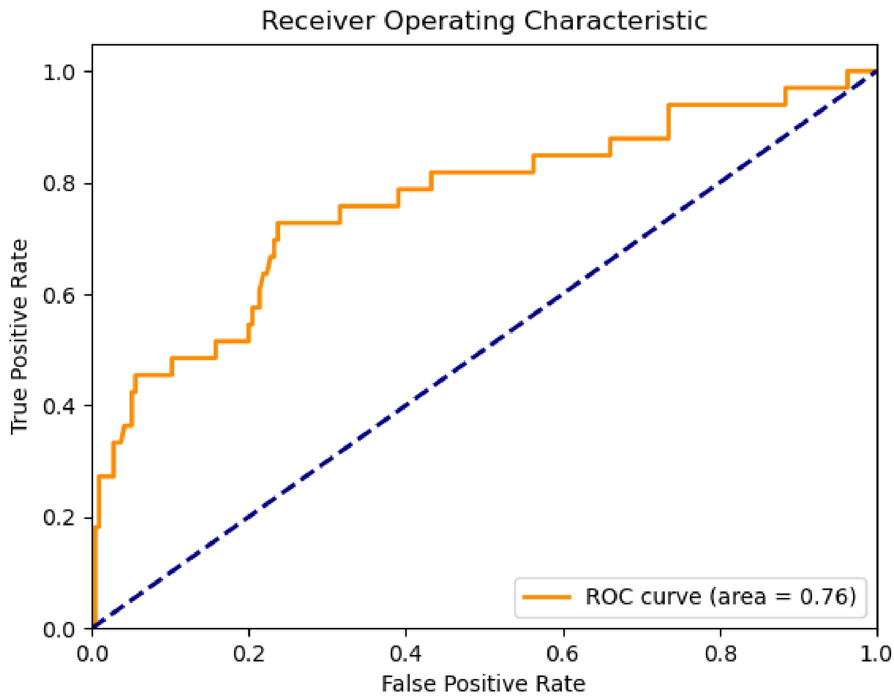

Figure 11: Receiver Operating Characteristic curve and Area Under the curve of the Random Forest Classification for predicting maternal mortality outcome.

The curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) at various threshold settings. The AUC is a single scalar value that summarizes the performance of the classifier across all threshold values. An AUC of 0.76 indicates that the Random Forest model has

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a satisfactory level of discrimination between those who experienced maternal death and those who did not. This means that there is a 76% chance that the model will correctly distinguish between a randomly chosen positive instance (maternal death) and a randomly chosen negative instance (no maternal death).

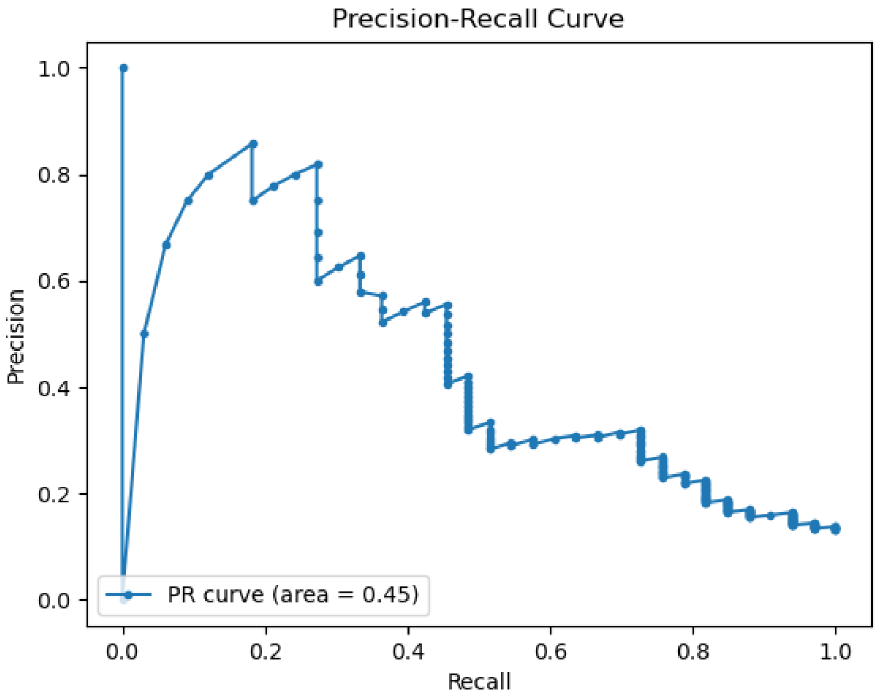

Figure 12: The precision-recall curve of the random forest classification model for predicting maternal mortality outcome.

Figure 12 presents the precision-recall (PR) curve for the Random Forest Classification model used to predict maternal mortality outcomes. Precision (y-axis) is the ratio of true positive predictions to the total number of positive predictions made by the model. Recall (x-axis) is the ratio of true positive predictions to the total actual positives. The AUC-PR is a single scalar value that summarizes the performance of the classifier across all threshold values in terms of precision and recall. An AUC-PR of 0.45 indicates the model's overall ability to maintain a balance between precision and recall.

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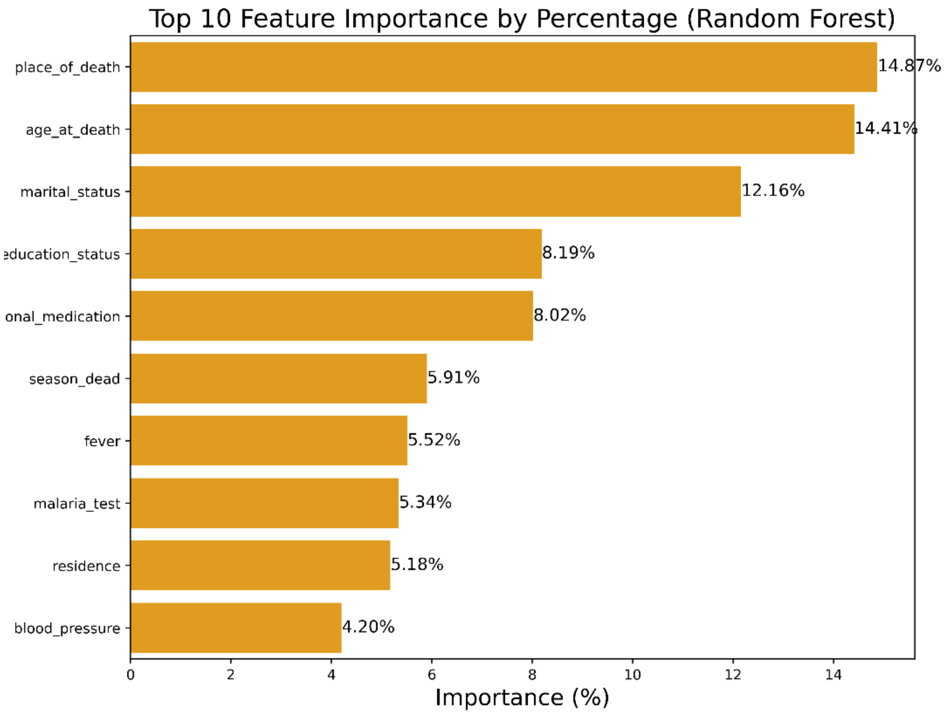

Figure 13: Top ten (10) feature importance in predicting maternal mortality using random forest algorithm.

In this model, the place of death is the most important feature, constituting 14.87% of the total feature importance. This reiterates the fact that maternal death mostly occurs within healthcare facilities because of the severities of complications that would have warranted women to seek hospital care in the first place. Age at death comes closest, with a feature importance of 14.41%, to state again that much younger women are disproportionately exposed to maternal mortality.

Other influential features considered are marital status, at 12.16%, education status, at 8.19%, and personal medication use, at 8.02%, which also highlight the complex socio-economic and health-related interplay of factors in maternal mortality. High importance of marital status agrees with findings that socio-cultural behaviors among married or cohabiting women may

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increase health risks, probably as a result of delayed healthcare access or particular health beliefs. This feature importance of personal medication also reflects that the role of traditional and self-prescribed medicines may be rather complex in maternal outcomes. While some of these practices may offer protective benefits, the practices should be valued in formal healthcare settings with considerations about safety.

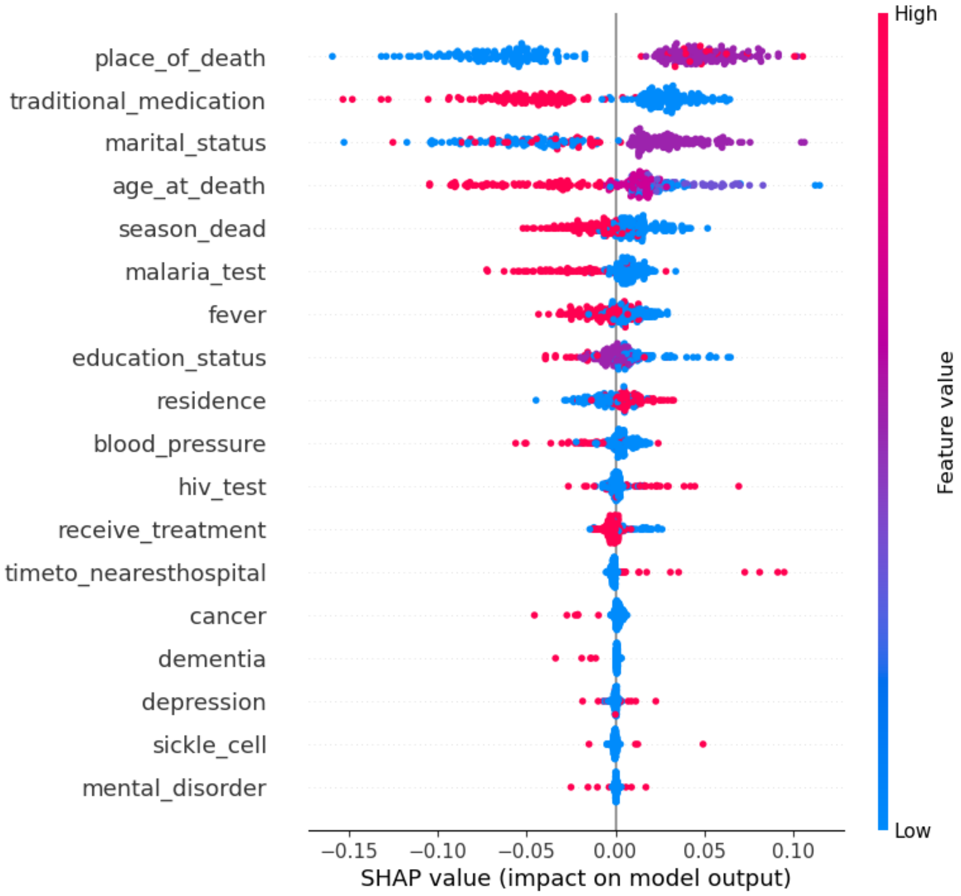

Figure 14: SHAP summary plot of feature impact on model prediction (Random forest).

This research uses SHAP analysis to interpret a Random Forest model's prediction for maternal mortality, identifying the most influential factors. The SHAP summary plot highlights **place of death**, **traditional medication**, **marital status**, and **age at death** as key contributors to

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predicting maternal mortality. For instance, maternal deaths are more likely in healthcare facilities, possibly due to the severity of cases treated there. Traditional medication appears to have a protective effect, while marital status and younger age increase risk, possibly linked to socio-cultural factors.

These insights help pinpoint high-risk groups and guide targeted interventions, such as improving emergency care in healthcare facilities, integrating safe traditional practices, and addressing risks for young mothers and married women. Overall, SHAP analysis enhances understanding of key factors influencing maternal mortality, aligning with the study's goal to inform data-driven policies for improving maternal health outcomes.

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Extreme Gradient Boost Classification

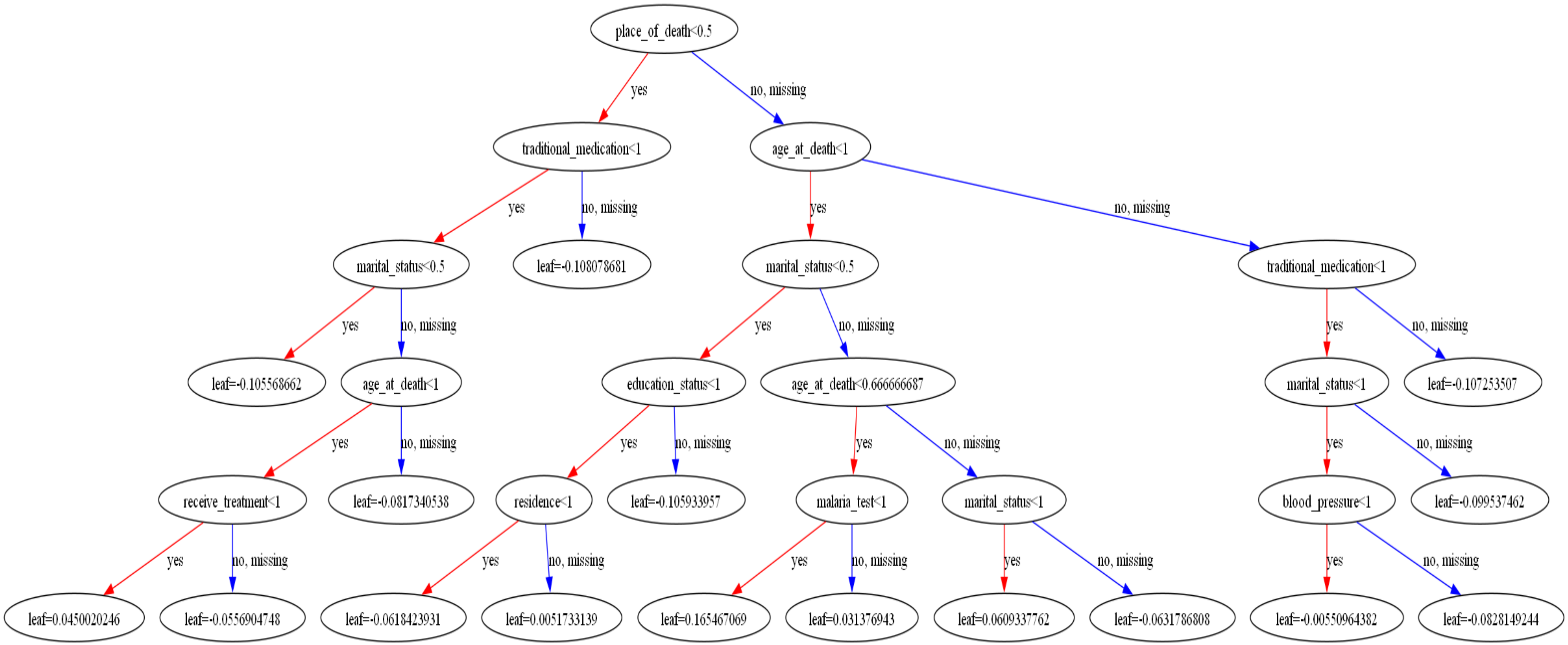

Figure 15: The Extreme Gradient Boost Classification analyse on the predicting of maternal mortality in Ghana.

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Figure 15 presents the results of an Extreme Gradient Boosting (XGBoost) classification visualization used to predict maternal mortality in Ghana. The XGBoost highlights the significant variables and decision nodes contributing to the prediction. The initial and most significant split is based on the place of death (Place of Death < 0.5). This indicates that the location where the death occurred is a critical factor in predicting maternal mortality. The model splits the data into two branches: deaths that occurred in a health facility and those that occurred elsewhere.

For deaths occurring in non-health facilities (place of death < 0.5), the next important split is whether traditional medication was used (traditional medication < 1). This shows the impact of using traditional medicine on maternal mortality, with the path further branching out based on this criterion. For the path where traditional medication was not used, marital status (Marital Status < 0.5) becomes a significant splitting factor. This indicates that marital status affects the likelihood of maternal mortality, with different risk profiles for married/cohabitating women versus single or separated/divorced/widowed women. The model further splits based on the age at death (Age at Death < 1). Age is a crucial factor, with younger women showing different risk profiles compared to older women.

Another significant factor is the education status (Education Status < 1). The model shows that women with different levels of educational attainment have varied risks of maternal mortality. The place of residence (Residence < 1) also plays a role, with urban and rural areas showing different risk profiles. The status of malaria testing (Malaria test < 1) further refines the prediction, indicating additional health-related risk factors.

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If the death occurred in a non-health facility, the model checks for the use of traditional medication. If traditional medication was used (Traditional Medication < 1), it further splits based on marital status, then age at death. If traditional medication was not used, it leads to a leaf node indicating the likelihood of maternal mortality. For deaths occurring in health facilities, the model checks the age at death. It further splits based on marital status, followed by education status and other factors. Leaf nodes represent the final prediction of the model. For instance, the leaf node's value of -0.108078681 indicates a lower likelihood of maternal mortality based on the paths leading to it.

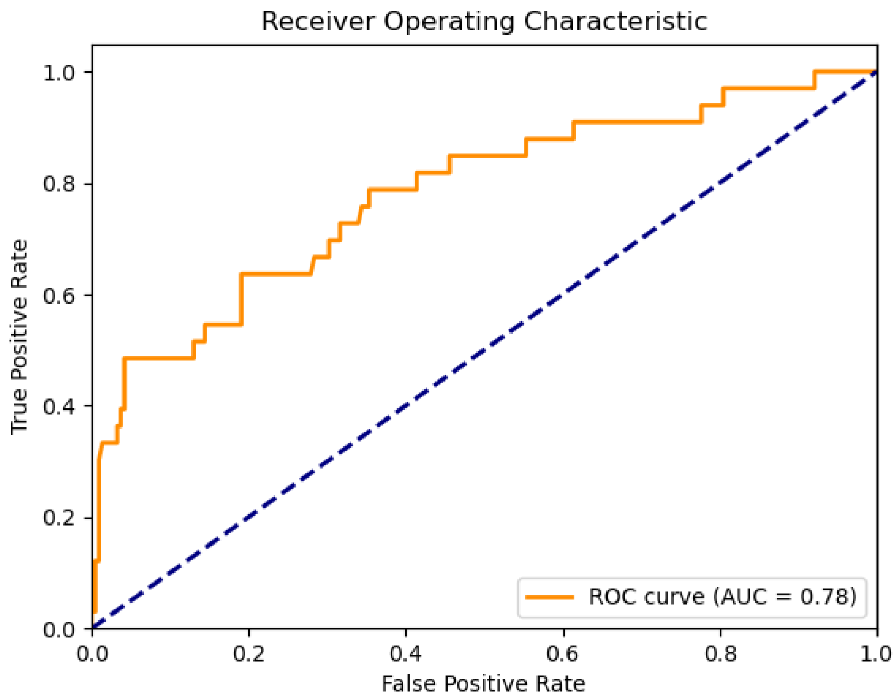

Figure 16: Receiver Operating Characteristic curve and Area Under the curve of the Extreme Gradient Boost Classification for predicting maternal mortality outcome.

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The AUC value of 0.78 indicates that the XGBoost model has a satisfactory level of discrimination between those who experienced maternal death and those who did not. This means there is a 78% chance that the model will correctly distinguish between a randomly chosen positive instance (maternal death) and a randomly chosen negative instance (no maternal death). This value is significantly better than random guessing and suggests that the model is quite effective in its predictions. The ROC curve itself shows the trade-off between the true positive rate and the false positive rate across different thresholds. A steeper curve that reaches the top-left corner quickly indicates a better-performing model. In this case, the curve suggests that the model maintains a relatively high true positive rate while keeping the false positive rate at a moderate level.

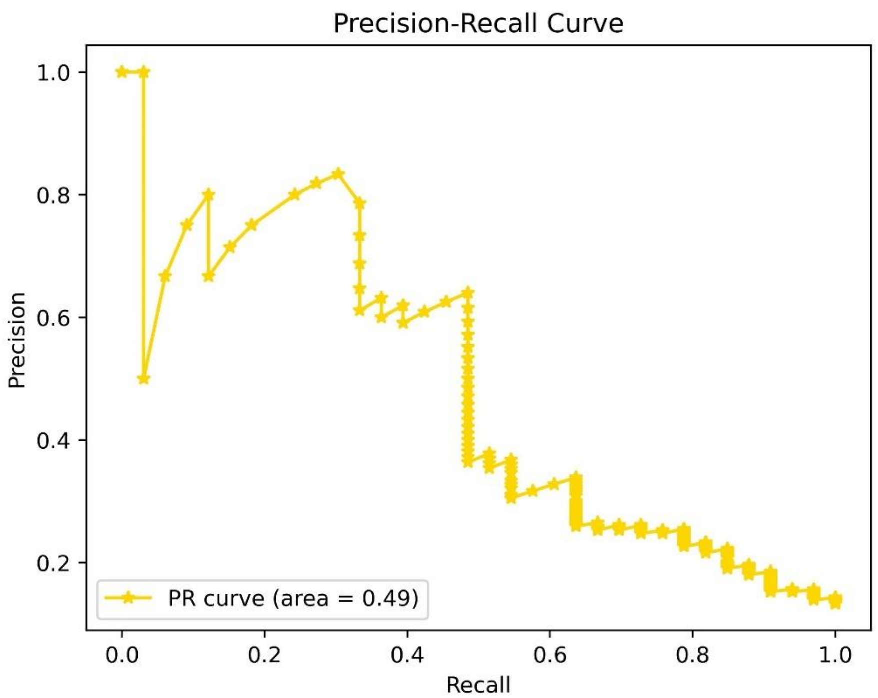

Figure 17: The precision-recall curve of the extreme gradient boost classification model for predicting maternal mortality outcome.

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The AUPRC value of 0.49 indicates a moderate level of performance by the XGBoost model in distinguishing between cases of maternal mortality and non-mortality. This value suggests that the model has some ability to correctly identify positive instances (maternal mortality), but there is room for improvement. The PR curve shows the trade-off between precision and recall. A higher precision at a lower recall indicates that when the model predicts a positive instance, it is often correct, but it might miss many actual positive instances. Conversely, higher recall at lower precision indicates that the model identifies most positive instances but also includes many false positives.

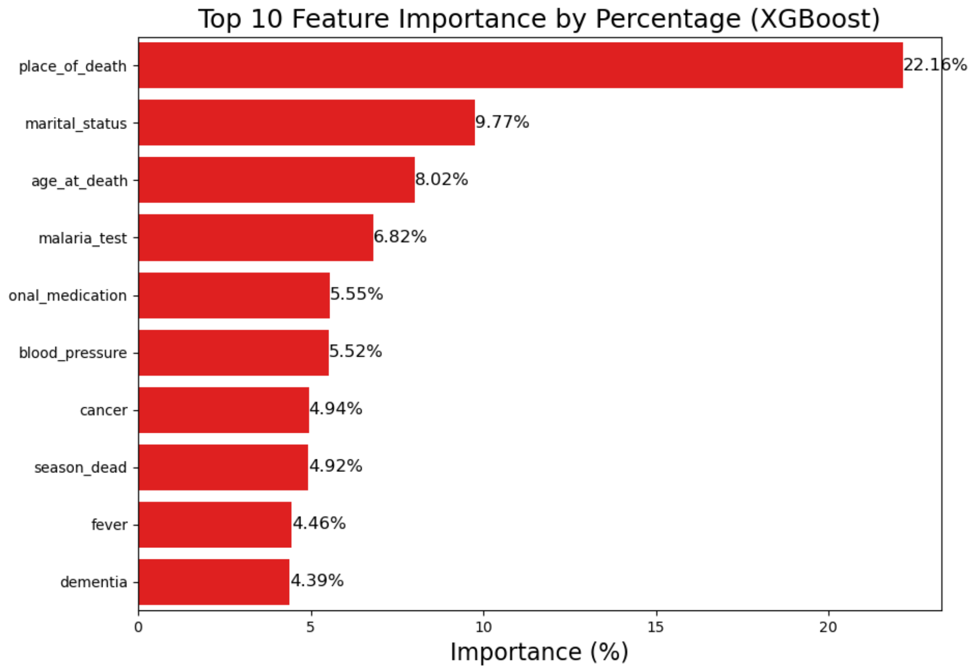

Figure 18: Top ten (10) feature importance in predicting maternal mortality using extreme gradient boosting.

This bar chart displays the top 10 features ranked by their importance in predicting maternal mortality in Ghana, as determined by the XGBoost algorithm. The XGBoost algorithm expresses each feature's importance as a percentage, indicating its relative contribution to the model's predictive power.

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In this research on maternal mortality in Ghana, XGBoost identified key factors that most significantly impact the likelihood of maternal death. The most critical feature is the "place of death," accounting for 22.16% of the total importance, indicating that where a woman dies (e.g., at home, in a health facility) is highly predictive of maternal mortality. This finding underscores the importance of healthcare accessibility and emergency response in reducing maternal deaths.

The next most influential factor is "marital status" (9.77%), which may reflect socio-cultural dynamics and healthcare-seeking behaviors. "Age at death" (8.02%) also plays a significant role, highlighting that age-related risks are crucial in maternal health outcomes. Other notable features include "malaria test," "traditional medication use," and "blood pressure," emphasizing the role of both infectious and non-infectious health conditions in maternal mortality risk. Lower on the list are conditions like "cancer," "season of death," "fever," and "dementia," each contributing between 4.39% and 5.52% of the importance. These findings suggest that both immediate health conditions and underlying medical history significantly influence maternal mortality risk.

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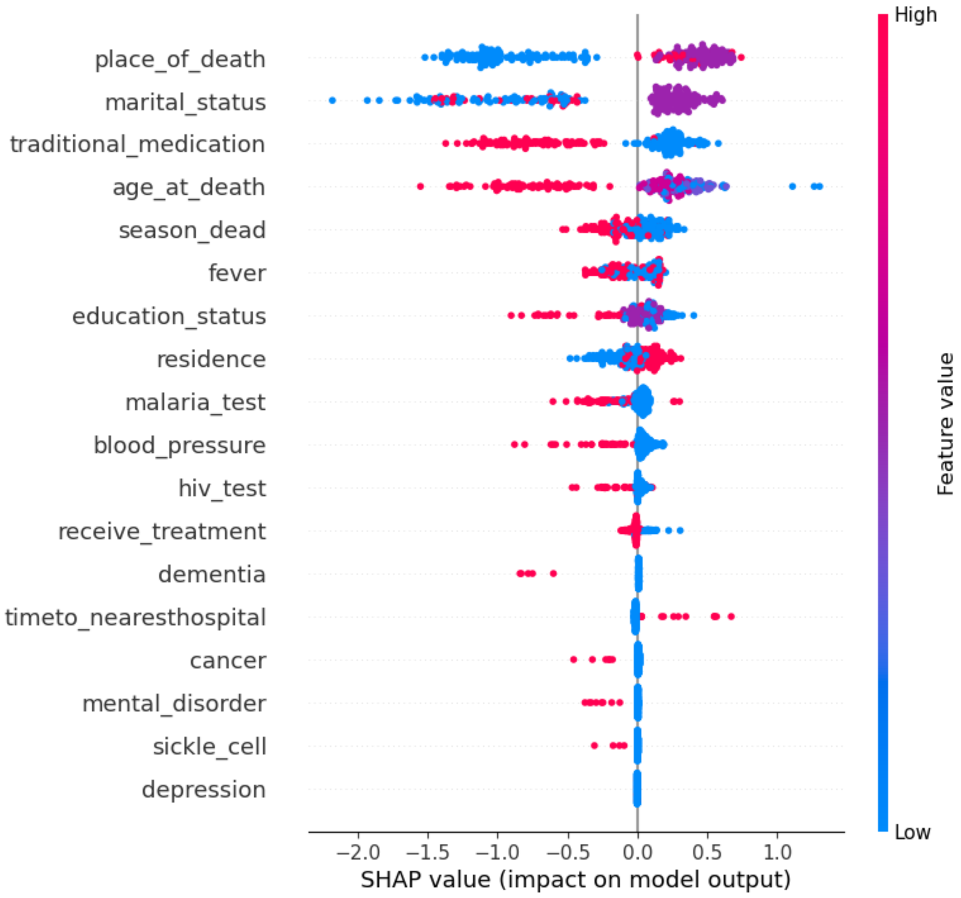

Figure 19: SHAP summary plot of feature impact on maternal mortality prediction.

This SHAP (SHapley Additive exPlanations) summary plot illustrates the impact of the top features on the model's predictions for maternal mortality. Each point represents a SHAP value for an individual prediction, showing how much each feature contributes to increasing or decreasing the likelihood of maternal death. The color gradient represents feature values, with high values in red and low values in blue. The horizontal axis shows the SHAP value, indicating the degree to which each feature impacts the prediction.

The spread for the Place of Death feature is big, hinting at this feature driving the model a lot. Increased values associated with dying in health facilities increase the risk of maternal death. Maybe this is because grave

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complications drive women towards places of healthcare where they finally die due to the serious states of their complications. Another very significant variable here is the marital status, where the higher values relate to being married or cohabiting; these variables usually tend to have a positive relationship to the probability of maternal mortality. Such results could be linked to the socio-cultural reasons that influence the health-seeking behavior among married women, which may be leading to increased risk. The social and economic commitments accompanying the marital status may place restrictions on access to timely and adequate health care, hence increasing vulnerability.

The plot also underlines the Traditional Medication variable: the higher the value, meaning the more traditional remedies used, the less the likelihood of maternal mortality, as can be viewed from the negative SHAP values. That result may reflect some protective effects of certain traditional practices, but it also points to the need to integrate safe traditional methods into the formal healthcare systems. This would improve health for women and decrease risks associated with maternal mortality.

Maternal mortality has a more complex relationship with Age at Death. Lower ages, represented by the color blue, have higher risks, as the higher values for SHAP show. That would seem to imply that younger women face certain risks and difficulties that greatly heighten their vulnerability to poor outcomes in maternal cases. It might be very significant to pay attention to the peculiar needs and vulnerabilities of this demographic when trying to bring down the rates of maternal mortality.

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Other factors, like season of death, fever, education status, and residence, show varied impacts on the maternal mortality predictions. For instance, fever has a tendency to have lower SHAP values for higher feature values, which may be indicative that cases with fever are easier to handle and, therefore, could yield better health outcomes. Features like blood pressure, HIV testing, and receiving treatment have varied influences, too, pointing toward health management as an important consideration in maternal health outcomes.

Research Objective Three

To ascertain which approach is superior in terms of fit and predictive ability, compare the outcomes from both statistical procedures (Logistic Regression) and data mining techniques (Random Forest Machine Learning and Extreme Gradient Boosting).

The primary aim of this study was to determine the superior approach in terms of fit and predictive ability by comparing the outcomes of statistical procedures (logistic regression) and data mining techniques (random forest machine learning and extreme gradient boosting). The study's findings are based on various cross-validation techniques, providing a comprehensive evaluation of each model's performance.

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Table 7: Diagnostic Test For the various Models

	Logistic Regression	**Random Forest Classification**	**Extreme Gradient Boost**
Test Accuracy	0.69	0.89	0.90
Test F1 Score	0.31	0. 30	0.41
Test Recall Score	0.52	0. 18	0.27
Test Precision Score	0.22	0.86	0.82
Jaccard Score	0.18	0.18	0.26
Log Loss	0.56	0.34	0.33
Confusion Matrix	155 60 16 17	214 1 27 6	213 2 24 9

According to Table 7, the accuracy of the models varies significantly. Logistic regression has an accuracy of 0.69, indicating that it correctly predicts maternal mortality cases 69% of the time. Random Forest improves upon this with an accuracy of 0.89, and XGBoost slightly outperforms Random Forest with an accuracy of 0.90. This suggests that both Random Forest and XGBoost are significantly better than logistic regression at correctly predicting maternal mortality cases.

The F1 score, which balances precision and recall, is 0.31 for logistic regression, 0.30 for Random Forest, and 0.41 for XGBoost. This metric is highest for XGBoost, indicating that it is the most reliable model in balancing false positives and false negatives. Logistic regression has the highest recall score at 0.52, meaning it is the best at identifying actual cases of maternal death. However, this comes at the cost of a higher rate of false positives. Random Forest and XGBoost have lower recall scores of 0.18 and 0.27,

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respectively, indicating that they miss more actual cases compared to logistic regression.

Random Forest has the highest precision score at 0.86, indicating it has the lowest rate of false positives. XGBoost also performs well with a precision score of 0.82. Logistic regression lags behind with a precision score of 0.22, meaning it has a higher rate of false positives compared to the other two models. The Jaccard Score, which measures the similarity between predicted and actual classifications, is 0.18 for logistic regression, 0.18 for random forest, and 0.26 for XGBoost. XGBoost has the highest Jaccard Score, indicating the best overall performance in terms of classification similarity. Log loss measures the accuracy of the probability predictions. Logistic Regression has a log loss of 0.56, Random Forest has a log loss of 0.34, and XGBoost has the lowest log loss at 0.33. A lower log loss indicates more accurate probability predictions, making XGBoost the most accurate in this regard.

Confusion Matrix Analysis

Logistic regression shows 17 true positives, 155 true negatives, 60 false positives, and 16 false negatives. This indicates that while it has a decent recall, it also has a significant number of false positives, leading to lower precision. Random Forest shows 6 true positives, 214 true negatives, 1 false positive, and 27 false negatives. It has very few false positives, which explains its high precision, but it misses many true cases, resulting in low recall. XGBoost shows 9 true positives, 213 true negatives, 2 false positives, and 24 false negatives. It balances false positives and false negatives better than

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Random Forest, resulting in better overall performance as indicated by the higher F1 score and Jaccard score.

In summary, based on the diagnostic metrics and confusion matrix analysis, XGBoost emerges as the most effective model for predicting maternal mortality in Ghana. It achieves the highest accuracy, F1 score, and Jaccard score, indicating a strong balance between precision and recall. While Random Forest shows high precision, its low recall suggests it may not be as reliable in identifying all true cases of maternal mortality. Logistic regression, despite having the highest recall, suffers from low precision and high log loss, making it less reliable overall.

Table 8: Cross Validation (Robustness Check)

	Logistic Regression	Random Forest Classification	Extreme Gradient Boost
Average KFold	0.8637	0.8750	0.8766
Average Stratified KFold	0.8629	0.8685	0.8790
Average Leave One Out	0.8629	0.8750	0.8762

In this study, the average KFold cross-validation score for logistic regression was 0.8637. This score indicates that, on average, the logistic regression model performs well across different subsets of the data. However, it is slightly less robust compared to the Random Forest and XGBoost models. In contrast, the Random Forest model had an average KFold score of 0.8750, demonstrating higher robustness and reliability compared to logistic regression. The XGBoost model achieved the highest average KFold score of 0.8766, indicating that it consistently performs the best across different data folds and provides the most reliable predictions among the three models.

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These results are consistent with existing literature, which highlights the superior performance of ensemble methods in handling complex data structures and interactions (Breiman, 2001; Chen & Guestrin, 2016).

The average stratified KFold score for logistic regression was 0.8629. This method ensures that each fold has a similar proportion of the target variable, showing that logistic regression is slightly less robust compared to Random Forest and XGBoost. Random Forest, with an average stratified KFold score of 0.8685, outperformed logistic regression, maintaining its reliability across stratified data subsets. The XGBoost model scored 0.8790, which is slightly higher than its KFold score and as well still higher than the other models, reinforcing its robustness and effectiveness. The use of stratified folds is crucial in ensuring that the model's performance is consistent across different population subgroups, thereby enhancing the generalizability of the results (Kuhn & Johnson, 2013).

The average Leave One Out cross-validation score for logistic regression was 0.8629. This method involves using each individual data point as a validation set once, showing the model’s performance on nearly every possible training data subset. While logistic regression is consistent, it is less robust compared to the other models. Random Forest demonstrated better robustness and reliability than Logistic Regression with a score of 0.8750. XGBoost achieved the second highest score of 0.8762, indicating the best overall performance and robustness when each data point is used as a validation set. LOO-CV provides a stringent test of model performance and the high score for XGBoost underscores its capacity to generalize well even under extensive validation conditions (James et al., 2013).

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Implications for Predictive Modeling in Maternal Mortality

The superior performance of the XGBoost model across all validation techniques highlights its capability in handling complex datasets typical of maternal health studies. The robustness of XGBoost is particularly beneficial in identifying critical predictors of maternal mortality, which can inform targeted interventions to improve maternal health outcomes (Bhutta et al., 2014). The findings align with recent advancements in machine learning applications in healthcare, which advocate for the use of ensemble methods to enhance predictive accuracy and reliability (Chen & Guestrin, 2016; Lundberg & Lee, 2017).

The significant factors identified through these models, such as marital status, place of death, and seasonal variations, underscore the multifaceted nature of maternal health determinants. The SDH model supports these findings, emphasizing the influence of socio-economic and environmental factors on health outcomes (WHO, 2008). Addressing these determinants requires a comprehensive approach that integrates improved healthcare access, gender equality, and socio-economic development to reduce maternal mortality rates effectively (Kruk et al., 2015).

In conclusion, based on the cross-validation results, the XGBoost model consistently outperformed both logistic regression and random forest classification across all validation techniques. The higher scores in KFold, Stratified KFold, and Leave One Out cross-validation indicate that XGBoost is the most robust and reliable model for predicting maternal mortality in Ghana. These findings highlight the potential of advanced machine learning techniques in enhancing predictive modeling and informing public health interventions to improve maternal health outcomes.

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CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

Introduction

This chapter synthesizes the study's findings, drawing conclusions from the results and discussing their implications for policy and future research. It highlights the critical factors influencing maternal mortality in Ghana, evaluates the predictive modeling techniques employed, and offers recommendations to inform policy and further research.

Summary of Results

The descriptive analysis provides an overview of the demographic and socioeconomic characteristics of the deceased women in the sample. The data set comprised 1,240 participants from various regions of Ghana, with a slightly higher representation from the Northern region (18.3%), followed by the Eastern (12.3%) and Volta (10.2%) regions. The deceased women were nearly evenly split between urban (47.5%) and rural (52.5%) residences. The majority of the women were Christian (68.0%), followed by Islam (20.4%), with small proportions practicing traditional/spiritualist beliefs (3.9%) or having no religion (7.7%).

In terms of age at death, the highest number of deaths occurred among women aged 30 to 39 years (34.9%), followed by those aged 40 to 49 years (31.4%), and 20 to 29 years (23.3%). Occupationally, most participants were engaged in sales and service work (53.3%) or skilled and unskilled labor (42.1%). Educationally, 55.6% had primary or basic education, 13.4% had secondary or tertiary education, and 31.0% never attended school. Marital

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status revealed that 59.6% were married or cohabitating, 25.1% were single, and 15.3% were separated, divorced, or widowed.

Health and illness characteristics showed that most women did not have cancer (95.7%), sickle cell disease (97.9%), or high blood pressure (86.0%). However, significant proportions had a fever (45.7%) or tested positive for malaria (25.2%). Most deaths occurred in health facilities (48.3%) or at home (42.6%), with a smaller proportion in other places (9.1%). The study aimed to determine the superior approach for predicting maternal mortality by comparing the performance of Logistic Regression, Random Forest Classification, and Extreme Gradient Boosting (XGBoost) models.

XGBoost achieved the highest average KFold score of 0.8766, indicating robust performance across different data subsets. Random Forest followed closely with a score of 0.8750, while logistic regression had a lower score of 0.8637. The stratified KFold results mirrored the KFold findings, with XGBoost scoring 0.8790, Random Forest 0.8685, and Logistic Regression 0.8629. This method ensures each fold has a similar proportion of the target variable. With respect to Leave One Out Cross-Validation (LOO-CV), XGBoost again demonstrated the highest score of 0.8762, followed by Random Forest at 0.8750 and Logistic Regression at 0.8629. LOO-CV involves using each individual data point as a validation set once, providing a stringent test of model performance.

XGBoost had the highest test accuracy at 0.90, indicating it correctly predicts maternal mortality cases 90% of the time. Random Forest had an accuracy of 0.89, and logistic regression had 0.69. XGBoost achieved the highest F1 score of 0.41, balancing precision and recall effectively. Random

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Forest had a lower F1 score of 0.30, and Logistic Regression had 0.31. Random Forest exhibited the highest precision at 0.86, indicating a low rate of false positives, but had a lower recall of 0.18, missing many actual cases. XGBoost had a precision of 0.82 and a recall of 0.27, balancing these metrics better. Logistic regression had the highest recall at 0.52 but a low precision of 0.22.

The logistic regression analysis identified several critical predictors of maternal mortality. Women who died in health facilities had significantly higher odds of maternal death compared to home deaths (AOR = 5.146, p = 0.000). Married or cohabitating women had higher odds of maternal death compared to single women (AOR = 5.481, p = 0.000). High blood pressure was associated with lower odds of maternal death (AOR = 0.532, p = 0.040). Use of traditional medication was linked to lower odds of maternal death (AOR = 0.467, p = 0.002). Having a fever was associated with lower odds of maternal death (AOR = 0.613, p = 0.022). Deaths in the wet season had lower odds compared to the dry season (AOR = 0.661, p = 0.032). Women aged 40 to 49 had lower odds of maternal death compared to those aged 0 to 19 years (AOR = 0.291, p = 0.010).

The results are consistent with existing literature that highlights the complex interplay of socio-economic, environmental, and health-related factors in determining maternal mortality (WHO, 2008; UN, 2015). The superior performance of advanced machine learning techniques like Random Forest and XGBoost in this study underscores their potential in handling complex datasets and capturing non-linear relationships, which are often

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missed by traditional statistical methods like logistic regression (Kuhn & Johnson, 2013; Breiman, 2001; Chen & Guestrin, 2016).

Conclusions

The study conclusively demonstrated that the Extreme Gradient Boosting (XGBoost) model is the most robust and reliable for predicting maternal mortality in Ghana. XGBoost consistently outperformed Logistic Regression and Random Forest across various validation techniques, including KFold, Stratified KFold, and Leave One Out cross-validation. The superior performance of XGBoost is attributed to its advanced machine learning capabilities, which enable it to handle complex interactions between covariates and capture non-linear relationships. This finding aligns with the literature on the efficacy of ensemble methods in predictive modeling, particularly in healthcare settings (Chen & Guestrin, 2016; Lundberg & Lee, 2017).

The analysis identified several critical risk factors for maternal mortality, emphasizing the multifaceted nature of maternal health determinants. These, including marital status and place of death, were significant predictors. Married or cohabitating women had a higher likelihood of maternal death compared to single women, highlighting the potential socio-cultural pressures and health risks associated with marital status. Additionally, deaths occurring in health facilities had significantly higher odds, suggesting that women who died in these settings might have experienced more severe complications requiring intensive medical intervention (Koblinsky et al., 2006; Ghana Health Service, 2021).

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High blood pressure and fever emerged as significant health-related predictors. Women with high blood pressure were less likely to die from maternal causes, potentially due to better management and early detection of hypertensive disorders during pregnancy. Fever, possibly indicating an ongoing infection, was also associated with lower odds of maternal death, suggesting effective management of infections in some cases (Abalos et al., 2013). Seasonal variations in maternal mortality were evident, with deaths occurring in the wet season having lower odds compared to the dry season. This finding suggests that environmental and seasonal factors play a crucial role in maternal health outcomes, necessitating seasonal preparedness and targeted healthcare interventions during different times of the year (UNICEF, 2016).

While several medical factors emerged as significant contributors to maternal mortality, notably those related to healthcare access and management of pregnancy-related complications, the investigation into mental health factors did not yield significant results. This outcome suggests that, within the scope of this study, mental health factors did not demonstrate a statistically significant association with maternal mortality rates. This finding aligns with existing literature that emphasizes the importance of medical conditions and healthcare accessibility in maternal health outcomes. It is crucial to acknowledge that mental health issues, while not statistically significant in this study, can still play a role in maternal health outcomes. The absence of significance may reflect the complexities involved in assessing mental health within the context of maternal care, such as underreporting, stigma, or challenges in data collection related to sensitive mental health issues.

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Recommendations

Enhanced Healthcare Access

To effectively reduce maternal mortality, policy efforts must prioritize improving access to quality maternal healthcare services, particularly in rural areas where healthcare infrastructure is often lacking. This includes:

- **Establishment of Comprehensive Emergency Obstetric Care Centers:** Policies should support the development and maintenance of more emergency obstetric care centers. These centers should be well-equipped with the necessary medical supplies and staffed by trained healthcare professionals who can handle high-risk pregnancies and complications.
- **Training Programs for Healthcare Providers:** Continuous professional development programs for healthcare providers should be implemented to ensure they are well-equipped with the latest knowledge and skills in maternal and neonatal care. This includes training on the management of hypertensive disorders, infections, and emergency obstetric procedures (WHO, 2020).

Integration of Traditional Medicine

The study found a significant association between the use of traditional medication and lower odds of maternal death. This highlights the importance of integrating beneficial traditional practices into the formal healthcare system:

- **Recognizing and Validating Traditional Practices:** Policies should aim to identify and validate traditional medical practices that have

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shown positive outcomes. This can be done through collaborative research involving traditional healers and medical professionals.

- **Training Traditional Practitioners:** Traditional healers should be trained to recognize high-risk pregnancies and encouraged to refer women to formal healthcare facilities when necessary. Integrating traditional healers into the formal healthcare system can enhance trust and cooperation between the community and healthcare providers (Ghana Ministry of Health, 2021).

Seasonal Preparedness

The study indicates that maternal deaths are lower during the wet season, suggesting the need for seasonal preparedness in maternal healthcare policies.

- **Ensuring Consistent Supply Chains for Medical Resources:** Policies should focus on maintaining a steady supply of essential medical supplies throughout the year, particularly during the dry season when the risk of maternal mortality is higher.
- **Enhancing Healthcare Infrastructure Resilience:** Healthcare facilities should be equipped to handle seasonal variations, such as increased disease prevalence during certain times of the year. This includes ensuring that infrastructure can withstand environmental changes and that there are adequate resources to manage seasonal health challenges (UNICEF, 2016).

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Focus on High-Risk Groups

Targeted interventions for high-risk groups, such as younger women and those with hypertension, are essential for reducing maternal mortality.

- **Programs for Adolescent Reproductive Health:** Policies should focus on developing and implementing programs that address the specific reproductive health needs of younger women. These programs should provide education on family planning, prenatal care, and the importance of seeking medical help during pregnancy (UNFPA, 2019).
- **Management of Hypertension:** Given the significant impact of hypertension on maternal mortality, policies should ensure that women receive regular blood pressure monitoring and management during pregnancy. This can be facilitated through the introduction of mobile health clinics and telemedicine services, particularly in rural areas (Abalos et al., 2013).

Broader Socio-Economic Policies

- **Addressing Socio-Economic Determinants:** Broader policies that address socioeconomic determinants of health, such as poverty, education, and social support, are necessary. These policies should aim to improve the overall living conditions of women, thereby reducing the risks associated with pregnancy and childbirth (WHO, 2008).
- **Community-Based Interventions:** Community health workers should be mobilized to educate women and their families about maternal health, encourage early and regular prenatal visits, and facilitate access to healthcare services. Community-based interventions can

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significantly enhance maternal health outcomes by ensuring that women receive timely and appropriate care (Lassi et al., 2016).

In conclusion, the findings of this study provide a comprehensive framework for policy interventions aimed at reducing maternal mortality in Ghana. By addressing the identified risk factors and implementing targeted interventions, policymakers can significantly improve maternal health outcomes and move closer to achieving the Sustainable Development Goals related to maternal health.

Suggestions for Further Research

- Future research should incorporate mental health variables such as anxiety and stress, as these factors can significantly impact maternal health outcomes. Mental health is often overlooked in maternal health studies, yet it plays a critical role in the overall well-being of pregnant women and new mothers. For example, incorporating standardized mental health assessments during prenatal visits can provide a more comprehensive understanding of the interplay between mental health and maternal mortality.
- Cultural practices and beliefs profoundly influence healthcare-seeking behavior and treatment adherence. Including variables related to cultural practices can enhance the predictive accuracy of models and provide insights into culturally sensitive interventions. For example, studying the impact of traditional birth practices, dietary restrictions, and the role of traditional birth attendants can offer valuable data on how cultural norms affect maternal health.

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- Future research should explore the application of deep learning techniques, such as neural networks, to improve the predictive power of maternal mortality models. These techniques can handle large, complex datasets and uncover intricate patterns. For example, utilizing convolutional neural networks (CNNs) to analyze medical imaging data (e.g., ultrasound images) alongside traditional health records to predict complications.

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