

Predictive models and under-five mortality determinants in Ethiopia: evidence from the 2016 Ethiopian Demographic and Health Survey

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Abstract

Background There is a dearth of literature on predictive models estimating under-five mortality risk in Ethiopia. In this study, we develop a spatial map and predictive models to predict the sociodemographic determinants of under-five mortality in Ethiopia. **Methods** The study data were drawn from the 2016 Ethiopian Demographic and Health Survey. We used machine learning algorithms such as random forest, logistic regression, and Cox-proportional hazard models to predict the sociodemographic risks for under-five mortality in Ethiopia. The Receiver Operating Characteristic curve was used to evaluate the predictive power of the models. **Results** There are considerable regional variations in under-five mortality rates in Ethiopia. The under-five mortality prediction ability was found to be 88.7% for the random forest model, 68.3% for the logistic regression model, and 68.0% for the Cox-Proportional Hazard model. Maternal age at birth, sex of a **child**, previous birth interval, water source, contraceptive use, health facility delivery services, antenatal and post-natal care checkups have been found to be significantly associated with under-five mortality in Ethiopia. **Conclusions** The random forest machine learning algorithm produces a higher predictive power for under-five mortality risk factors for the study sample. There is a need to improve the quality and access to health care services to enhance **childhood** survival chances in the country.

Background

Globally, 5.6 million children under the age of 5 died in 2016. The global under-five mortality rate declined by 56 percent, from 93 deaths per 1,000 live births in 1990 to 41 in 2016. Still, the under-five mortality rate in low-income countries was 73.1 deaths per 1000 live births in 2016—almost 14 times the average rate in high-income countries (5.3 deaths per 1000 live births) [1]. It has been observed that more than half these deaths are due to infectious diseases (such as pneumonia and diarrhea) that are preventable and treatable through simple, affordable interventions [2].

Sub-Saharan Africa has been identified as the region with the highest level of under-five mortality in the world, with about 41% of global under-five mortality burden [3]. As a result, the under-five mortality rate in sub-Saharan Africa remains highest in the world despite its decline over the past decades [4]. Ethiopia has been found to have the fifth-highest number of newborn deaths in the world, following India, Pakistan, Nigeria, and the Democratic Republic of Congo [5]. It is estimated that about 472,000 children die in Ethiopia each year before their fifth birthday, which places Ethiopia sixth among the countries in the world in terms of an absolute number of under-five deaths [6]. In Ethiopia, the under-5 mortality rate has declined by two thirds from the 1990 figure of 204/1,000 live births to 58/1,000 live births in 2016, and thus, achieving the target for Millennium Development Goal 4 (MDG 4) [7]. Despite this achievement, the under-five mortality rate in Ethiopia is still higher than those of many low and middle-income countries (LMIC).

Previous studies have provided much evidence on the socioeconomic and demographic factors that are associated with under-five mortality in Ethiopia [8–10], using traditional regression models. In this study,

we ascertain the determinants of under-five mortality in Ethiopia using non-traditional regression models drawing on nationally representative data. Specifically, we employed machine learning techniques to compare the results of three popular regression models: a logistic regression model, a cox-proportional hazard model, and a random forest model. The main aim is to determine the best predictive model and highlight the potential of machine learning techniques in estimating the sociodemographic effects on under-five mortality in future research. Also, we initially develop a spatial map for crude under-five mortality rate by region in Ethiopia. The goal is to visually highlight the spatial disparities in under-five mortality in the country and to inform and strengthen appropriate policies or intervention strategies aimed at reducing under-5 mortality in the country.

Methods

Data source

This study draws on data from the 2016 Ethiopian Demographic and Health Survey (EDHS), the most recent in the demographic and health survey series that is conducted every five years. The EDHS is a nationally representative household survey that collects data on a wide range of population, health and nutrition indicators with the aim of improving maternal and child health in Ethiopia [11]. The survey used a multi-stage stratified sampling technique based on the 2007 National Population and Housing Census of Ethiopia to select respondents from a total of 624 clusters (187 urban and 437 rural) [11]. A total of 10,641 children under age 5 of mothers selected from 645 clusters were included in this study. This was based on retrospective information obtained from mothers about children that died under age five within the five years preceding the survey (2011 to 2016).

Study variables

In this study, the outcome variable—under-five mortality—was measured in two ways to suit the three different models used. For the logistic regression and random forest models, the primary outcome of interest was under-five mortality categorized as being alive (coded as 0) or dead (coded as 1). Under-five mortality was also defined as the death of a child after birth through 59 months of life for the Cox-Proportional Hazard Model.

The predictors used in this study include community, household, individual and health services factors. The community factors comprised residence type (urban/rural) and geographical region (Tigray, Afar, Amhara, Oromia, Somali, Benishangul-Gumuz, Southern Nations Nationalities and People Region (SNNPR), Gambella, Harari, Dire Dawa, and Addis Ababa). The household factors used were the source of drinking water (improved/unimproved), toilet facility (improved/unimproved) and household wealth (poor, middle, rich). The individual-level factors consisted of maternal and child characteristics. Maternal factors include mother's age at birth (<20, 20–29, 30–39, 40–49), education (No education, primary, secondary/higher), contraceptive use (Yes/No) and mother's nutritional status measured by her body

mass index (BMI) (underweight/overweight and normal). Child factors were the sex of the child, health facility's delivery services (Facility with Cesarean Section (CS) services, facility without CS, home), birth order (1–2, 3/later) and previous birth interval (<2, 2–4, >4 years). The health services factors included the desire for previous pregnancy (child wanted then, wanted later, not at all), antenatal visits (0, 1–4, 5+ visits), and postnatal visits within two months after delivery (Yes/No). The selection of these predictor variables was based on information from existing literature on the subject.

Analytic strategy

The R programming language (version 3.6.0) was used to perform the data processing and analysis. We first developed a spatial map for crude under-five mortality rates by regions in Ethiopia to document the regional disparities in under-five mortality in the country. In this regard, we aggregated the number of under-five deaths by region and then merged them with an Ethiopian regional shapefile before mapping it.

We also used the widely accepted machine learning algorithms—logistic regression, random forest, and Cox-proportional hazard model—to predict under-five mortality in Ethiopia. Machine learning techniques build models based on previous observations which can then be used to predict new data. Thus, the model built is a result of a learning process that extracts useful information from the data generation process of the previous observations [12]. It provides an opportunity for a cheaper, faster, and a better way of predicting population health problems [13] and considered to be the most prominent application of artificial intelligence technology for ensuring good health and social care for an entire population through preventive strategies, and protection from diseases [14].

The models were trained and tested using a set of features extracted from the datasets housed in the 2016 Ethiopian Demographic Health Survey. These algorithms were trained and tested using the national representative data can identify at-risk of childhood undernutrition more accurately. In all the experiments, measures of performance were performed on a 30% random sample of test data, which were not used in cross-validation or model selection. With the remaining 70% of the data, 10-fold cross-validation was used to tune the model parameters. The performance of these algorithms was evaluated using various metrics such as precision, and Area Under Curve (AUC) and Receiver Operating Characteristic (ROC) curve, thus, giving us a good indicator to validate the results.

Results

Descriptive results of the background characteristics

Of the 10,641 under-five children in the sample, 5.3% were reported to have died within the study period. More than half of the children were males and close to half belonged to mothers aged between 20–29. The majority of the children were from rural settings (89%) and belonged to women without formal education (66.1%). The majority (75.1%) of children belonged to mothers who wanted their child by then. About 47% of the children were from poor households and 68.7% belonged to women who were not using

any form of contraceptive methods at the time of the survey. About 73 percent of the children were delivered at home while the rest were delivered at a health facility. While about 63% had made antenatal care checkups before delivery, only 8.3% had made postnatal care checkups after delivery.

Spatial distribution of under-five mortality

Figure 1 shows the spatial distribution of crude under-five mortality rates by regions in Ethiopia. The under-five mortality rate in the map is presented as a number of under-five deaths per 1000 live births. The Afar region recorded the highest under-five mortality rate of 125 per 1000 live births, followed by Benshangul–Gumuz, and Somali, which recorded 98 and 94 per 1000 live births respectively. The lowest under-five mortality rate is recorded in Addis Ababa, with a rate of 39 per 1000 live births.

Predicting under-five mortality

Below, we report results from the three machine learning models (regularized logistic regression, Random Forests, and Cox-Proportional Hazard model) to predict the under-five mortality outcome. The under-five mortality prediction accuracy was found to be 96.4% for the Random Forest model, 79% for the logistic regression model, and 53% for the Cox-Proportional Hazard model. Results for the area under the ROC curve (AUC) for the ROC are shown in Figure 1. Of the three machine learning models employed in this study, the Random Forest model was found to be the best with the predictive ability of 88.7%. The performance results for the logistic and Cox-Proportional Hazard Models were similar and comparable. However, a modest gain was obtained in the case of the Random Forest model.

Determinants of under-five mortality

Both the hazard ratios and logistic regression models revealed that mother's age at first birth, child's sex, preceding birth interval, water source, contraceptive use, combined mode of delivery, antenatal care checkup, and postnatal care checkups within two months after delivery were all common factors associated with under-five mortality. Table 2 shows a summary of the results for the logistic regression model. Children of mothers who had higher age at first birth (20+ years) had lower odds of under-five mortality [OR: 0.62, CI: (0.29, 0.65)] compared with children of teenage mothers (<20 years). Male children are 1.93 times (CI: 1.38–2.72) more likely to die under the age of five compared with their female counterparts. Birth order had no significant association with under-five mortality albeit higher order appeared to have higher odds of under-five mortality. Children of higher preceding birth intervals [> 2 years] had lower odds [OR: 0.44, CI: (0.29, 0.65)] of under-5 mortality compared with children of lower preceding birth interval (< 2 years). Children from households with an improved source of water had also had lower odds [OR: 0.55, CI: (0.39, 0.79)] of under-five mortality compared with their counterparts from households with an unimproved source of water. However, type of toilet facility, residence, mother's

education, household wealth, region, nutritional status, and child wanted had no significant association with under-five mortality.

Children of mothers who did not use contraceptive had increased odds [OR:1.62, CI: (1.09, 2.45)] of under-five mortality compared with children of mothers used modern contraceptive methods. Similarly, children of mothers who delivered at facilities without CS services had increased odds [OR: 2.79, CI: (1.36, 6.07)] of under-five mortality compared with children of mothers who delivered at CS facilities. Children of mothers who received antenatal care checkups before delivery and postnatal care checkups after delivery had significantly lower odds of dying [OR: 0.63, CI: (0.44, 0.91), and OR: 0.40, CI: (0.13, 0.95), respectively], compared with children of mothers who did not receive any antenatal and postnatal care checkups.

Discussion

The study develops a spatial map and a predictive model to investigate risk factors for under-five mortality in Ethiopia using machine learning techniques. The spatial map provides evidence of considerable regional disparities in under-five mortality rates in Ethiopia similar to what has been found in Ghana [15]. Tigray and some regions in the central part of the country show the lowest under-five mortality rates whereas regions in the eastern and western parts of the country have the highest under-five mortality rates. Providing evidence on the underlying risk factors may help to better understand the spatial variations of under-five mortality in the country. Regarding the predictive model, the prediction accuracies and AUC statistics are found to be comparable across all models. Modest gains have been obtained in the case of the random forest model followed by the logistic regression model. It shows the high predictive power of the new machine learning algorithm (Random Forest Model) compared to the earlier models (Logistic and cox-Proportional Hazard) in predicting under-five mortality risks. Machine learning techniques have been said to provide a cheaper, faster, better, and prolific way of predicting population health problems [13]. In effect, this study underscores the significant role played by machine learning techniques in the estimation of the population health risks and provides promising directions for future research.

The hazard ratios and logistic regression models show that mother's age at first birth, child's sex, preceding birth interval, water source, contraceptive use, combined mode of delivery, antenatal care checkup, and postnatal care are significantly associated with under-five mortality in Ethiopia. In this study, children of teenage mothers show a higher risk of under-five mortality than children of older mothers. Consequently, teenage motherhood is associated with increased under-five mortality risk [16]. However, much-existing evidence also shows that there is a higher under-five mortality risk of giving birth at both young and old ages [16, 17]. Additionally, male children have shown a significantly higher risk of dying before age five compared with female children. This is consistent with the finding of a cross-sectional study conducted in Bangladesh [18]. It has been shown that male children have an increased risk of dying in the first month of life because of high vulnerability to infectious disease. This is because female neonates are more likely to develop early fetal lung maturity in the first week of life, which may result in a lower incidence of respiratory diseases in female compared with male neonates [19]. Also, the

risk of under-five mortality has increased significantly among children with less than 2 years preceding birth interval than children with more than 2 years or birth interval. Affirmatively, there is much evidence that longer birth intervals improve the survival chance of succeeding children [17, 20]. A short preceding birth interval can be said to influence under-five mortality through three main mechanisms: First, closely spaced births may cause depletion of the mother. The second mechanism is through sibling competition while the third is the transmission of infectious diseases between the closely spaced children [21]. While the first mechanism is biological, and the last two are said to be behavioural effects of a short preceding birth interval [22].

Furthermore, this study finds that the use of an unimproved source of drinking water is associated with increased risk of under-five mortality. Lack of access to clean water has been considered as one of the important factors that contribute to more than 80 percent of child deaths in the world [23]. There is also considerable evidence from studies in developing countries that show that household sanitation and a clean water supply promote child health and survival [24, 25]. In Ethiopia, the proportion of the population using improved drinking-water sources is only 57%, and those who use improved sanitation is less than five percent [2]. This may have serious implications for the under-five mortality levels in the country. This study further provides evidence that children whose mothers do not use any contraceptives have a significantly higher risk for under-five mortality than their counterparts whose mothers use modern contraceptives. A number of studies have found favorable effects of contraceptive use in reducing under-five mortality [15, 18, 26]. Contraceptive use may be associated with a reduction in under-five mortality because it may help to reduce unplanned pregnancies as well as high-risk births that may likely lead to under-five mortality. Modern contraceptive use, thus, plays a crucial role in the reduction of under-five mortality in Ethiopia.

This study also finds that delivery in health facilities without CS services and at home is associated with higher under-five mortality risk. This may be mainly related to dealing with delivery complications that may raise under-five mortality risk. Health facilities with CS services are very scarce in Ethiopia; even where they are available, transportation challenges encourage women to deliver at home delivery when facility-based delivery is available at a minimal cost [27]. Moreover, this study provides evidence of the positive effect of antenatal and postnatal care checkups on under-five survival chances. This is a confirmation of the significant association observed between antenatal attendance and lower under-five mortality risk in the literature [28]. The implication is that children whose mothers do not receive antenatal and postnatal care services may experience more proximate under-five mortality risk factors, such as congenital and infectious diseases, than their counterparts.

This study is not without limitations. The survey comprised only surviving women, and since neonatal and maternal mortalities may occur concurrently, this may have led to an underestimation of the under-five mortality rates. Also, using a cross-sectional survey data such as the DHS only provides a snapshot of the scenario unlike like using a longitudinal approach. Despite these limitations, this study provides a strong case for using machine learning techniques to model or predict the underlying risk factors of under-five mortality in a population.

Conclusions

This study provides evidence of considerable regional disparities in under-five mortality rates in Ethiopia, with the highest rates observed in the Afar, Benishangul–Gumuz and Somali regions. In this study, the Random Forest Model—a newer machine learning algorithm—provides a modestly higher predictive power than the earlier ones such as the logistic and Cox-proportional hazard models in predicting under-five mortality risks in Ethiopia. Under-five mortality in Ethiopia is significantly associated with maternal age at first birth, sex of a child, previous birth interval, water source, contraceptive use, health facility delivery services, antenatal and post-natal care checkups. Children of teenage mothers and mothers who do not use contraceptives, male children, short birth interval children, children from unimproved water source households, children delivered at facilities without CS services as well as children whose mothers do not receive antenatal and post-natal care all have increased risks for under-five mortality in Ethiopia. This study highlights the potential of machine learning methods in predicting under-five mortality risk factors and points to crucial areas for policy development. Our findings reinforce the need to improve the quality and access to health care services such as antenatal, delivery, and post-natal care as well as family planning services in the country to enhance childhood survival chances. Also, based on the findings, expanding access to improved drinking water will help to substantially reduce under-five mortality in the country in the future.

Abbreviations

AUC, Area Under Curve; BMI, Body Mass Index; CS, Caesarean Section; EDHS, Ethiopian Demographic and Health Survey; LMIC, Low and Middle-income Countries; MDG, Millennium Development Goal; ROC, Receiver Operating Characteristic; SNNPR, Southern Nations Nationalities and People Region.

Declarations

Ethics approval and consent to participate

The study used secondary data from the EDHS. Ethical approval not applicable.

Consent to publish

Not applicable

Availability of data and methods

The dataset analysed in this study are available on The DHS Program website.

Competing interests

The authors declare that they have no competing interest.

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Authors' contributions

FB conceived and designed the study. FB and SHN performed the analysis with technical support from LP and CSS. FB wrote the initial draft of the manuscript with technical support from SHN, LP and CSS. All authors critically reviewed the manuscript for important intellectual content and then approved the final version of the manuscript for publication.

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Tables

Table 1 Percentage of sociodemographic characteristics of the study sample

Characteristics	Percent (N= 10,641)
Child Survival Status	
Alive	94.9
Dead	5.1
Child Sex	
Female	48.1
Male	51.9
Age of the mother	
15-19	3.4
20-29	49.2
30-39	38.6
40-49	8.8
Residence	
Rural	89.0
Urban	11.0
Education	
No education	66.1
Primary	26.8
Secondary and Higher	7.1
Wealth index	
Poor	46.8
Middle	20.7
Rich	32.5
Combined mode of delivery Services	
Fac with CS delivery	18.5
Fac without CS delivery	9.0
Home	72.5
Contraceptive use	
Yes	31.3

No	68.7
Child Wanted	
Then	75.1
Later	16.7
Not at all	8.1
Antenatal visits	
No Visit	37.1
1-4 visits	46.6
5+ Visits	16.3
Postnatal care visits	
No	91.7
Yes	8.3

Table 2: Results from the logistic regression model

	95% CI			p-value	Sig
	OR	Lower	Upper		
Age at first birth (Ref: <20 Years)					
20+years	0.62	0.42	0.89	0.01	**
Child sex (Ref: Female)					
Male	1.93	1.38	2.72	0.00	***
Birth order (Ref: 1-2)					
3rd or later	1.56	0.92	2.80	0.11	
Birth interval (Ref: <2 Yrs)					
2-4 yrs	0.44	0.29	0.65	0.00	***
>4 yrs	0.44	0.25	0.77	0.00	***
Water source (Ref: Unimproved)					
improved	0.55	0.39	0.79	0.00	***
Toilet facility (Ref: Improved)					
Unimproved	1.57	0.74	3.84	0.28	
Residence (Ref: Rural)					
Urban	0.81	0.30	1.93	0.66	
Education (Ref: No Education)					
Primary	0.79	0.50	1.20	0.28	
Secondary and Higher	1.75	0.64	4.24	0.24	
Wealth index (Ref: Poor)					
Middle	0.94	0.61	1.44	0.79	
Rich	1.10	0.72	1.66	0.66	
Contraceptive use (Ref: Yes)					
No	1.62	1.09	2.45	0.02	*
Region (Ref: Oromia)					
Addis Ababa	0.84	0.08	147.27	0.91	
Afar	0.59	0.02	121.68	0.77	
Amhara	0.73	0.07	125.14	0.84	

Ben-Gumuz	1.26	0.13	215.23	0.88	
Dire Dawa	0.71	0.06	125.31	0.83	
Gambella	0.77	0.03	153.23	0.88	
Harari	1.19	0.12	203.49	0.91	
SNNP	0.87	0.00	267.05	0.96	
Somali	1.23	0.05	253.49	0.91	
Tigray	0.92	0.00	258.46	0.97	
Nutritional status (Ref: Normal)					
Overweight	0.66	0.25	1.45	0.35	
Underweight	1.11	0.75	1.62	0.58	
Facility delivery services (Ref: Fac with CS Services)					
Facility without CS delivery	2.89	1.36	6.07	0.01	**
Home	1.20	0.72	2.12	0.50	
Antenatal visits					
1-4 visits	0.63	0.44	0.91	0.02	*
5+ Visits	0.46	0.24	0.82	0.01	.
Postnatal care (Ref: No)					
Yes	0.40	0.13	0.95	0.07	.
Child wanted (Ref: Then)					
Later	0.74	0.45	1.17	0.21	
Not at all	1.41	0.88	2.17	0.14	

OR: Odds Ratios; Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1.

Figures

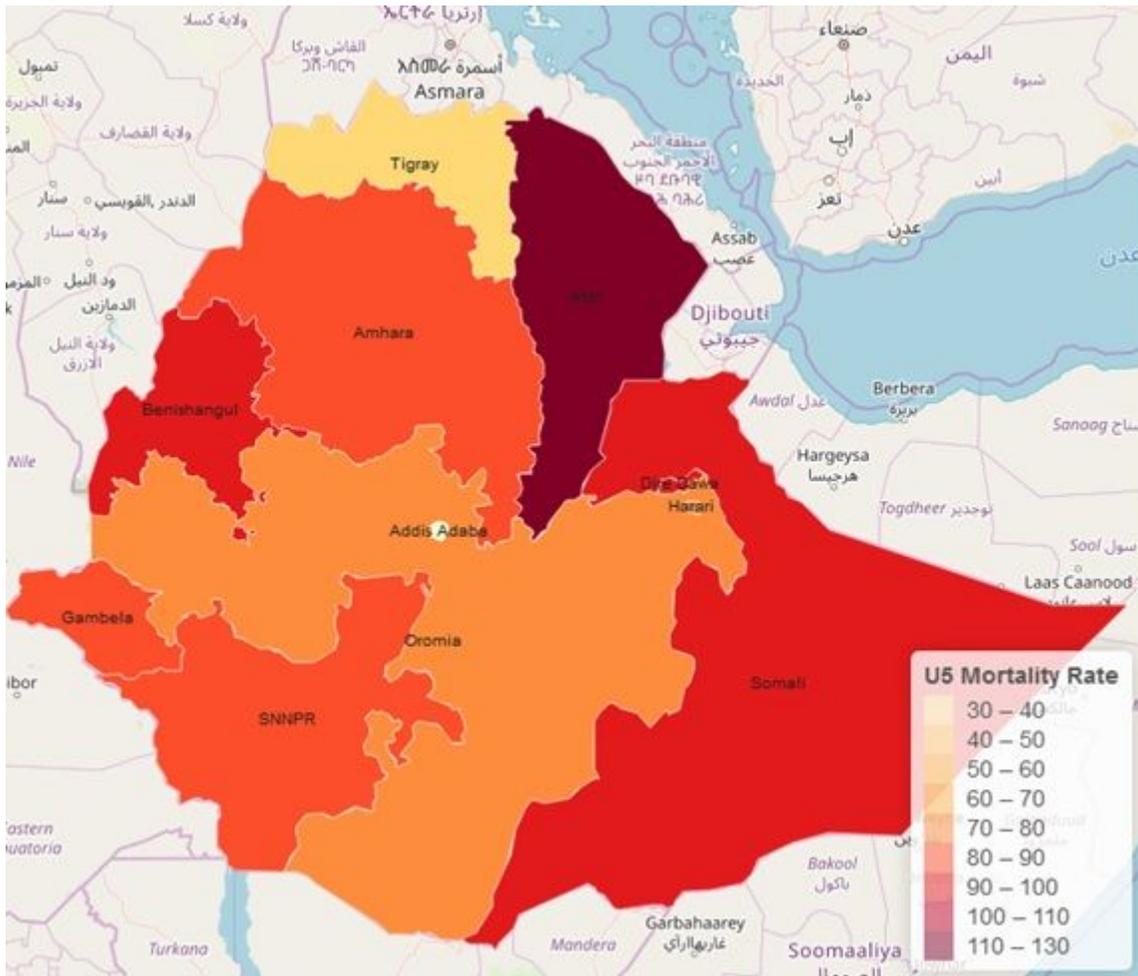


Figure 1

Fig 1: Spatial distribution of crude under-five mortality rates by regions in Ethiopia. Source: Developed by the authors.

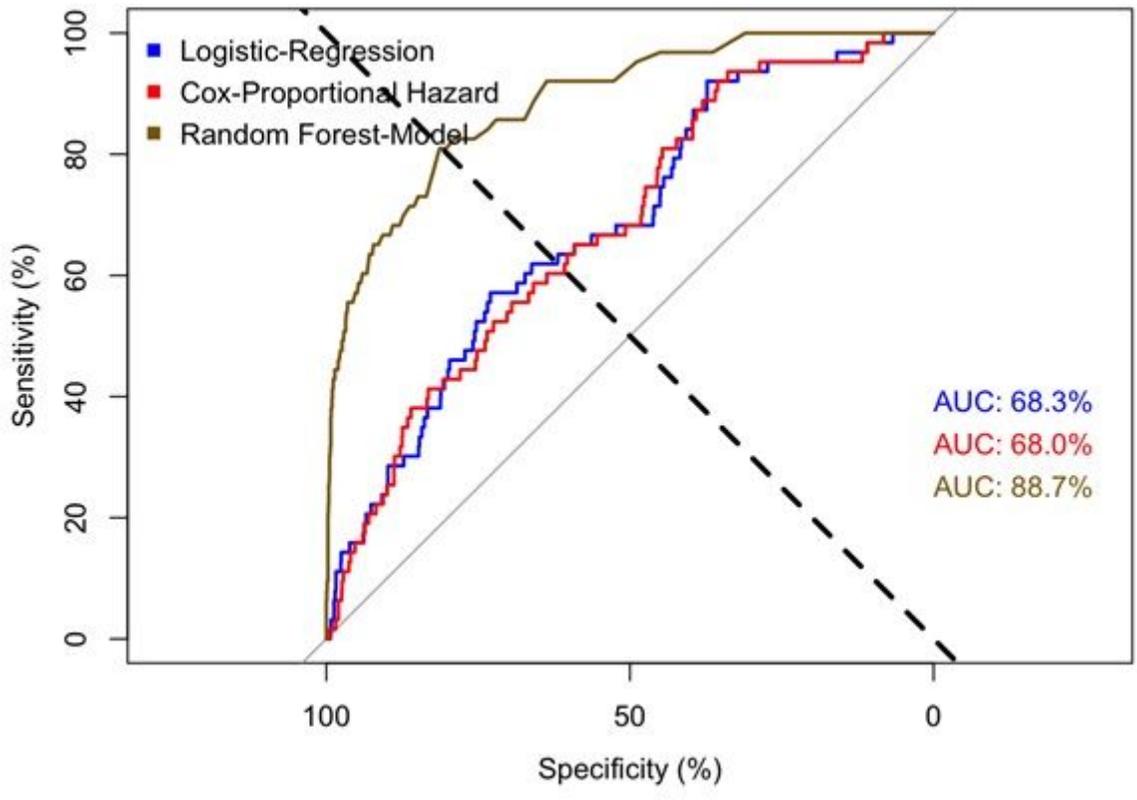


Figure 2

Figure 2: ROC Curves for the three models