## 1. Introduction

### 1.1 Problem Motivation

The United Nations and other international organisations have recognised that high rates of death due to complications from pregnancy and childbirth is an ongoing, critical global health challenge [3]. As a result, they have set numerous goals and resolutions to encourage countries to take substantive action to reduce maternal mortality [3]. Despite the number of maternal deaths decreasing by 40% between 2000 and 2023, maternal mortality remains unacceptably high [3]. In 2023, one woman was estimated to die from complications due to pregnancy and childbirth every two minutes [3]. Many of these deaths were avoidable, with almost 3 million women predicted to have died from preventable, maternity-related causes between 2010 and 2020 [37]. The vast majority of deaths attributed to complications from pregnancy and childbirth occur in low and lower-middle income countries due to substantial country-level inequities [4]. For example, a woman in Australia or New Zealand is 400 times less likely to die from giving birth than a woman in sub-Saharan Africa [3].

Further reduction in the rate of maternal mortality has stalled, with only two regions (central and south Asia, and Australia and New Zealand) showing continued decrease in the rate of maternal mortality between 2016 and 2023 [37]. All other regions either experienced no change or increases in the rate of maternal mortality [37]. Researchers and international organisations have emphasised how sparse, low-quality data about maternal mortality has hindered effective interventions, as maternal mortality is often substantially underestimated in official statistics [3, 4, 10, 21, 22, 38]. As a result, in 2015, the World Health Organisation highlighted the need to improve measurement of maternal mortality in its Strategies toward Ending Maternal Mortality report [4, 21].

### 1.2 Existing Maternal Mortality Modelling Solutions

To address this data gap, the United Nation’s Maternal Mortality Inter-Agency Group and the Institute of Health Metrics and Evaluation formulated models that estimate maternal mortality ratios (MMR), or the number of maternal deaths per 100,000 live births, on a global scale [28, 29]. These models use classical machine learning techniques that are heavily informed by statistics [28, 29]. In contrast, the more recently published Global Maternal Health Microsimulation model estimates MMR by simulating the reproductive lifecycles of thousands of individual women [32]. These models were developed using domain specific knowledge [28, 29 , 31].

All three of these models make assumptions about the underlying data distribution, which may bias their MMR predictions. For example, the models assume a certain degree of regional homogeneity, especially when estimating the MMR of countries with sparse data. Additionally, the most widely used models only consider a small subset of variables that impact maternal mortality and assume that the relationships between their chosen covariates and maternal mortality are globally applicable [28, 29]. These assumptions may reduce the accuracy of their MMR predictions.

Due to their differing methodologies, the three models sometimes produce dissimilar MMR estimates [43]. At times, their MMR estimates differ by hundreds of deaths per 100,000 live births [43]. These contradictory results can cause confusion about which set of estimates to use and reduce trust in the modelling process, hampering policy makers’ ability to effectively use the models’ MMR predictions [42].

These limitations motivate the central question of my thesis: “*Can an alternative, interpretable modelling technique that does not make assumptions about the underlying data distribution and that considers a wide variety of socio-economic and health-related variables be used to estimate maternal mortality ratios?*”

### 1.3 Alternative Solution - Contributions of My Research to the Literature

This question motivated the primary aims of my research:

1. To use interpretable machine learning methods to estimate countries’ maternal mortality ratios and assist in global MMR monitoring.
2. To identify important socio-economic and health-related features to inform targeted policies that will most reduce MMR.

To address these aims, I developed, tested, and compared a series of alternative machine learning models to estimate MMR. I based all proposed models on the decision-tree architecture because decision trees can effectively handle high-dimensional, sparse data without making assumptions about the underlying data distribution [35]. These properties were essential given the high proportion of missing data and large number of feature variables in my data. While deep learning methods also have strong performance on high-dimensional data, they cannot natively handle sparse data and I did not want to risk introducing bias into my dataset by removing or imputing the missing values [39, 41]. Therefore, no deep learning was used in this research.

The main contributions of my research to the literature were that:

* **I developed decision-tree based Random Forest, XGBoost, and LightGBM models that can effectively deal with sparse data to estimate and forecast MMR.** I found that the specific training data used to fit the models had a greater impact on their predictive accuracy than the choice of model type, feature selection strategy, or proportion of missing data included in the dataset.

* **I used stacking and voting ensemble methods to combine predictions from 300 Random Forest, LightGBM, and XGBoost models fit on different training data to further improve predictive accuracy.** The best-performing ensemble leveraged patterns learned by each component model on the various training datasets. I found that the Random Forest Stacking Ensemble had the highest overall predictive performance, with higher performance gains observed when the performance of the models being combined was less uniform.
* **I examined the performance of the best-performing ensemble when it was trained on data from all income levels versus a specific income level**. Estimates of past MMR values were more accurate when informed by trends across all income levels while MMR forecasts were more accurate when based on income-specific data. Generally, the lowest mean-squared error was achieved when predicting the MMR of higher-income countries.
* **I benchmarked my models’ MMR predictions against estimates from existing maternal mortality models in the literature.** While my predictions were broadly similar to the literature’s estimates, they tended to predict lower MMR values due to methodological differences, variation in model variables, and possible underestimation of MMR in my ground truth data.
* **I designed the Python code** used to implement and evaluate these models. The code is **freely available on GitHub** at

https://github.com/R0sle/health\_economics\_honours. Model training and evaluation was performed on the National Computational Infrastructure’s **Gadi Supercomputer**.

* **I determined the socio-economic and health-related features with the highest predictive power for MMR**, many of which were established risk factors. I used these results and existing causal research to suggest that investment in women’s education, incentives for skilled medical personnel to practice in rural areas, and increased provision of family planning services would reduce MMR by addressing important drivers of maternal mortality.
* Using my models, **I provided alternative MMR estimates for 172 countries between 1985 and 2018**. These estimates can be used to resolve existing disagreement about the true maternal mortality ratios and inform scientific debate about the relative merits of different MMR modelling approaches.
* **I showed that my models achieved comparable MMR predictive accuracy to existing models in the literature without a similarly heavy reliance on domain knowledge**. Therefore, my models have wider applicability in low resource countries where domain knowledge in this field is still developing.