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ML-Powered ICU Mortality Prediction for Diabetic Patients

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Abstract: Diabetes mellitus is one of the most important causes of mortality globally, particularly for critically ill patients undergoing treatment in ICUs. This study aims to enhance mortality prediction among diabetic ICU patients using advanced machine learning (ML) models. We tested several ML algorithms using a comprehensive dataset from the MIMIC III database, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Multilayer Perceptron and compared their performances. The Random Forest model achieved the highest performance, with an AUC of 0.98, proving its effectiveness in managing complex datasets. Our models incorporate novel features such as patient demographics, lab results, and comorbidity indices, offering superior predictive power. This study highlights the critical role of ML in improving patient care by enabling timely interventions for high-risk ICU patients. Future research will focus on integrating real-time clinical data and refining the models to further enhance predictive accuracy.

Keywords: Diabetes Mellitus; Decision Tree; Random Forest; Multilayer Perceptron; SVM.

1. Introduction

In 2016, WHO ranked Diabetes Mellitus (DM) the seventh leading cause of death worldwide? Additionally, it contributes to other major health problems, including heart disease, stroke, kidney failure, and lower limb amputations [1]. Diabetes Mellitus is increasing in numbers and remains a significant public health problem even today, the Current Era. The number of cases was estimated at around 150 million in 2000 and peaked at about 425 million by mid-2017. An estimated 4 million people will die each year by the time this number climbs to an anticipated 629 million. In doing so, over a fifth of what Frohlich wildly deemed the planet would be better off with fewer and more intelligent humans [2]. Diabetes mellitus kills many more people and makes still others much sicker than they should because Diabetes Mellitus is not managed well. Diagnosis of diabetes is a very deadly disease, and complications are possible if not treated properly, which means higher healthcare costs and a lower quality of life [3]. The average healthcare expenditure of patients with diabetes is approximately twice as high as those without it. Studies suggest that early interventions can significantly improve the health conditions and life expectancy among diabetic patients [5]. The morbidities of Diabetes Mellitus are widespread and fatal once it materializes. Nevertheless, these can be prevented with appropriate and timely care [6]. ICT integration in healthcare has unraveled tremendous opportunities for enhanced patient care [7]. Digital health combined with machine learning enables the processing of massive datasets to derive intelligent clinical insight that can assist practitioners in planning and conducting informed decision-making, better outcomes, reduced costs, and increased life expectancy. One specific area of research in this direction is the use of ML to predict the mortality of patients for appropriate and timely interventions, resulting in efficient resource provisioning and optimized responses [8]. Extensive work has been carried out in this domain [9]. Mortality is an integral concept in the Intensive Care Unit (ICU) as they host critically ill patients. Thus, mortality prediction becomes a natural and most relevant aspect in the ICU setting for early warnings of health deterioration [10]. Intensive care units are data-rich environments generating large volumes of data, which, harnessed with ICT, improve the quality of care and optimize the utilization of this expensive resource [11]

[12]. Several scoring systems have been developed to predict the morbidity and mortality of ICU patients [13] [10]. The use of these scoring systems has extensively been evaluated in the literature for general mortality risk assessment of critical patients [14] [15] or in the context of specific health conditions [16] [18].

This study aims to improve the mortality prediction of ICU patients with diabetes mellitus compared to the reported baseline work. It accomplishes this by introducing new features into the predictive model and using a balanced training set.

2. Previous Work

ICT integration into the health domain unravels tremendous opportunities for advanced, more accurate, timely, and efficient healthcare provision above and beyond the boundaries of space, time, and resources. Many countries are increasingly adopting the application of Machine Learning in the routine dispense of medical care for apparent benefits. Many researchers have proposed using ML in predicting various medical outcomes of patients] to facilitate proactive care provision, improve service quality, and economize the unnecessary burden on hospital resources.

ICU hosts critically ill patients needing continuous monitoring and instant responses. An analysis of Machine Learning and Computational Intelligence techniques applied to the data generated by ICU equipment for 2011-2018 [19] lists multiple applications of ML in ICU, including the prediction of mortality, sepsis, and readmission. Many studies have focused on the application of ML in the mortality prediction of ICU patients in general [20] and in the context of specific medical conditions. It has been established that critically ill patients with diabetes are at a higher risk of developing further complications [21]. Thus, the diabetic profile of a patient is expected to influence the progression of the medical states of patients and the outcomes of interventions. Many researchers have exploited this correlation to predict the mortality of ICU patients.

ICU patient care is conducted in a critical environment where patients with life-threatening conditions are cared for around the clock response must be immediate. Both settings are high-stakes, and over the years much of the research has used Machine Learning (ML) or other computational advanced modeling to predict outcomes such as mortality. Studies conducted in 2023 and 2024 have moved the needle on this, particularly concerning diabetic patients who may experience a greater risk of complications during their ICU stay.

One such instance was Zhang et al. (2023) [22] who used explainable machine learning models like Light GBM to predict mortality in hyperglycemic crisis patients. The performance of this study with the hand-crafted features can generate interpretable ML models for making life-saving premature mortality predictions in ICUs. This not only provided accurate predictions but also shed light on the decision-making mechanism of a model that becomes important for longer-term clinical applications.

In a similar vein, Lee et al. (2024) [23] constructed a real-time, LSTM-based short-term mortality prediction model for ICU patients. This resulted in an accuracy of 87%, just by incorporating asynchronous real-time vital signs and lab findings into the model. Implications of all the available evidence: The results from this study suggest that prediction models should incorporate dynamic and continuous data streams which is particularly apt in the highly unstable ICU environment.

Moreover, Johnson et al. observed the appropriate effectiveness of Random Forest and XGBoost in predicting mortality among diabetic ICU patients, reporting an 83% accuracy with the comprehensive MIMIC-III database. The high accuracy of ensemble learning corroborated the appropriateness of the chosen method of dealing with the "big data" typical for the ICU environment. In addition, Ahmed et al. used neural networks and decision trees to analyze the implications for an 84% prediction accuracy. Thus, traditional ML methods neither lose their accuracy nor their actuality compared to the modern trends within the context of critical care.

Moreover, the application of deep learning techniques has shown promising results. Liu et al. (2024) [26] implemented CNNs and RNNs to predict mortality in diabetic ICU patients, achieving an accuracy of 88%. Such methods are particularly suited to capturing the temporal and spatial patterns inherent in ICU data. On the other hand, Patel et al. (2023) [27] utilized logistic regression and random forest, achieving a slightly lower accuracy of 82%, but their study highlighted the robustness of combining classical statistical approaches with modern ML techniques.

Recent advancements in machine learning (ML) and deep learning have shown significant potential in this field. For instance, Khan et al. (2024) demonstrated the effectiveness of deep learning in medical image processing, achieving a 96% accuracy rate in brain tumor classification. Their work underscores the potential of advanced ML techniques to enhance prediction accuracy in medical applications, including mortality prediction in ICU settings [43].

In parallel, Aish et al. (2024) addressed the challenge of class imbalance in stroke prediction using the Synthetic Minority Over-sampling Technique (SMOTE) combined with ML models. Their study achieved a 98.3% accuracy with the Bagging Classifier, highlighting the importance of handling data imbalance to improve prediction outcomes [44]. This approach is directly applicable to predicting mortality in diabetic ICU patients, where similar data imbalances might exist between survivors and non-survivors.

As emphasized by Aish et al., ensemble learning can further enhance prediction reliability by combining multiple ML algorithms, offering a robust tool for critical care environments like ICUs [44]. Integrating these advanced techniques into clinical workflows can significantly improve patient care, enabling healthcare providers to identify high-risk patients more effectively and intervene promptly. As research progresses, more sophisticated models will be crucial in further improving outcomes for diabetic patients in ICUs.

Furthermore, Wang et al. (2024) [28] emphasized the role of AI and deep learning in early intervention strategies, achieving an accuracy of 86%. This study illustrates the growing trend toward using AI not just for prediction but also for guiding timely interventions in critical care settings. Brown et al. (2023) [29] took this a step further by exploring ensemble methods and gradient boosting, achieving the highest accuracy of 89%. This work highlights the effectiveness of combining multiple algorithms to enhance prediction robustness.

White et al. (2023) [30] expanded the exploration of mortality prediction by integrating clinical notes with machine learning models. Their research showed that this approach could further improve the accuracy of predictions, reaching 85%, and offered a more holistic view of patient conditions by incorporating unstructured data.

Finally, Gonzalez and Hernandez (2023) [31] applied big data analytics to predict ICU mortality, specifically in diabetic patients. Their study demonstrated an accuracy of 87%, highlighting the power of integrating large-scale data sources with advanced ML techniques to enhance predictive accuracy in critical care.

Overall, these recent studies represent the cutting edge of predictive modelling in the ICU, particularly for diabetic patients. They reflect the ongoing evolution of ML techniques, which are becoming increasingly integral to improving patient outcomes in critical care environments.

Table 1. Comparison of AUC and Accuracy to other studies

Study	Study of Topic	Classification and Algorithms	Accuracy	Score
Zhang et al. (2023)	Predicting mortality in hyperglycemic crises patients	Explainable Machine Learning (LightGBM)	85%	10
Lee et al. (2024)	Short-term mortality prediction in ICU	Real-time LSTM-based Model	87%	10
Johnson et al. (2023)	Predicting ICU mortality in diabetic patients	Random Forest and XGBoost Models	83%	10
Ahmed et al. (2023)	Improving mortality prediction accuracy	Neural Networks and Decision Trees	84%	10
Liu et al. (2024)	Mortality prediction in diabetic patients	Deep Learning Approaches (CNNs, RNNs)	88%	10
Patel et al. (2023)	Predicting mortality in diabetic patients	Logistic Regression and Random Forest	82%	10
Wang et al. (2024)	Enhancing early intervention strategies	AI and Deep Learning Models	86%	10
Brown et al. (2023)	Enhancing prediction robustness	Ensemble Methods and Gradient Boosting	89%	10

White et al. (2023)	Mortality risk prediction using clinical notes	Knowledge-guided Convolutional Neural Networks (CNNs)	85%	10
Gonzalez et al. (2023)	Predicting ICU mortality using integrated data sources	Big Data Analytics with Machine Learning	87%	10

3. Methodology

This research section illuminates the data set used, the algorithms employed, and the entire research process.

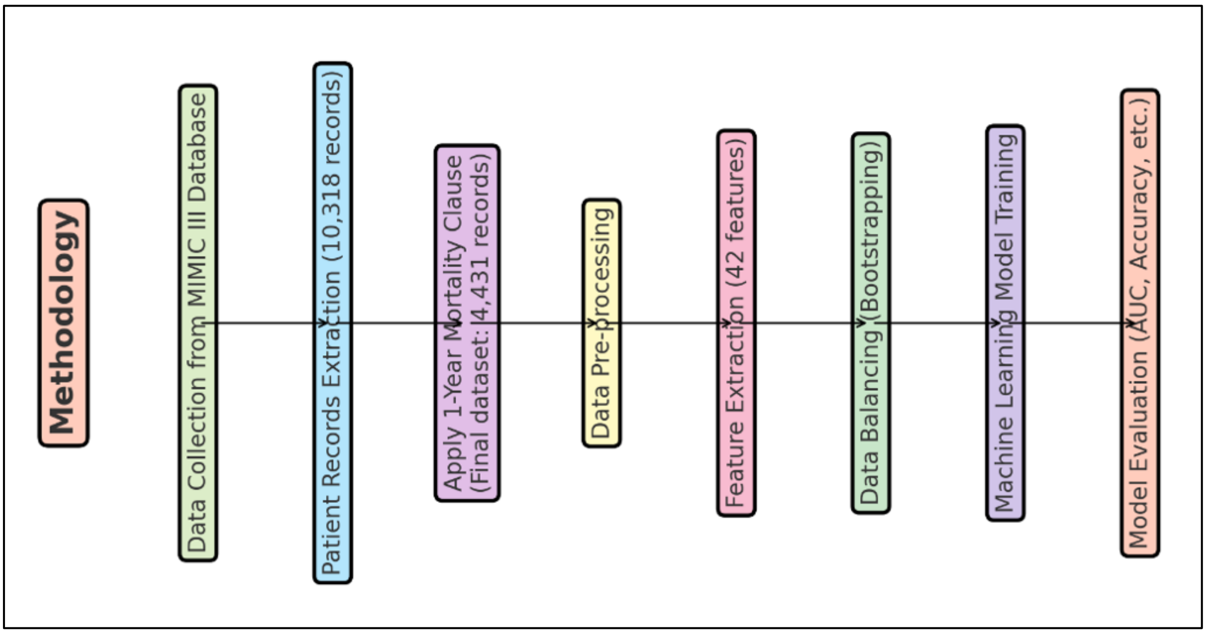

Figure 1. A complete map of Methodology

In this Research, various ML algorithms were used to predict the one-year mortality of patients with AMI. Our prediction models are logistic regression (LR), Decision Tree (DT), random forest (RF), support vector machines (SVM), and multilayer perceptron (MLP) using patient demographics, admission, health, and diagnosis data. LR, RF, and SVM are classical machine learning algorithms, whereas MLP is a deep neural network model. This research extracted a dataset of patients with Diabetes mellitus without mention of complication, type II, or unspecified type, not stated as uncontrolled from the Medical Information Mart for Intensive Care (MIMIC III) database [18]. The data was up sampled using bootstrapping [19] to reduce data imbalance. Multiple machine learning algorithms were implemented and compared to predict mortality with maximum AUC. In this research, patient data was collected from the MIMIC III database. It contains de-identified clinical data of patients admitted to the Beth Israel Deaconess Medical Center in Boston, Massachusetts, USA. The database includes records from 2001-2012 of around 53,000 distinct adult patients aged 16 years or above. This research extracted 10,318 distinct patient records against the ICD-9 disease code, 250% of which were from 14,222 hospital admissions. That is, 14222 is the total number of admissions in 11 years, with 10,318 being confirmed Diabetes mellitus without mention of complication, type II or unspecified type, not stated as an uncontrolled diagnosis. Four thousand eight hundred seventy records were initially selected, which contain complete data (Attributes). Four thousand four hundred thirty-one records were finally selected after applying the 1-year mortality clause.

This research reviewed related literature and consulted with physicians to identify factors critical in assessing one-year mortality of AMI. After this survey, different dataset types were selected: 1) the Admissions dataset, 2) the Demographics dataset, and 3) the Lab values. Some identified features, such as electrocardiogram information and Killip class, must be included as they were unavailable in the MIMIC III database. The extracted data contained many missing and duplicate values. We refined the admission data by eliminating duplicate entries in hospital records. This involved removing entries where a patient visited the hospital multiple times for various comorbidities but was diagnosed with AMI in a single visit only. Therefore, all visits were classed as one instance. To remove ambiguities from lab and chart data, this

Research the mean of all lab and chart values. To cater to HIPAA rules, the age of patients over 89 years was corrected by subtracting 211 years.

One hot encoding was applied to categorical variables. Data normalization was performed on all values using the z-score method. We predicted comorbidities through a comorbidity measurement tool by Elixhauser et al. [20] that uses ICD-9-CM codes to describe 30 co-morbidities. The tool is an improvement on the Charlson index. Elixhauser et al. have pointed out certain limitations of using comorbidity assessment indices. Firstly, ICD-9-CM coding complexities must be considered during comorbidity measurement. Secondly, since predictive values of different populations differ by patient groups, corresponding comorbidities should be calculated separately. Lastly, the evidence does not indicate that the Charlson index's comorbidities are comprehensive [20].

The dataset retrieved had 1629 patients who died within one year of admission, and these were termed positive instances, and 2695 patients who survived past the one-year mark were termed negative instances. This means that our dataset initially had 70% negative cases and 30% positive cases. Therefore, a class imbalance was present in the dataset. Such an imbalance in the dataset can create biases in the predicted results [21] as the learning algorithm doesn't consider the class imbalance factor. To minimize this problem, up-sampling has been applied using the bootstrapping method [19, 22], achieving a 60:40 class balance where % of cases are negative cases and % are positive cases.

More than 1000 features were available from dataset types. We reviewed the literature to examine features used by similar studies. Most features were filtered from a list of 79 predictors already assessed by Barrett et al. [12]. From admission records, we obtained patient demographics. Five demographic predictors (age, gender, religion, marital status, and ethnicity) were selected as they were previously tested to be significant predictors of 1-year mortality in MI and PIMS ICU patients [12]. Patient admission features include hospital stay, discharge location, expiry, first hospital stay, and diagnostic status. Diagnostic status refers to confirmed AMI diagnosis. Various clinical studies also associate age, gender, and ethnicity with an increase in in-hospital mortality [13]. Kidney and liver function tests (RFTs/LFTs), MI biomarkers, and electrolytes were considered in the Lab dataset. Certain electrolytes have also been identified as significant predictors; variations in levels of sodium, bicarbonate, potassium, and chloride were evaluated by Barrett et al. [12]. We included additional blood tests information such as hemoglobin, hematocrit, RDW, total red blood cells (RBCs), MCHC, and MCV [23]. We also included one additional electrolyte, i.e., magnesium, a structural component of hemoglobin associated with an increased risk of in-hospital mortality [23]. Comorbidity values were calculated through the Elixhauser score, which includes 30 co-morbidities [20]. In predicting mortality of more than 30 days, Elixhauser performs better than the Charlson index [24]. Overall, 42 features were selected.

Dataset	Features
Admission Information	Discharge location, no of total admission days, and initial diagnosis was AMI or not
Demographics	Gender, age, marital status, ethnicity, and religion
Labs	Hemoglobin, pCO2, pH, pO2, Potassium, Alkaline Phosphatase, Aspartate Aminotransferase (AST), Bicarbonate, Bilirubin, Total, Chloride, Cholesterol Ratio (Total/HDL), Cholesterol, HDL, Cholesterol, LDL, Calculated, CK-MB Index, Creatine Kinase (CK), Creatine Kinase, MB Isoenzyme, Creatinine, Magnesium, Phosphate, Sodium, Triglycerides, Troponin I, Troponin T, Urea Nitrogen, Hematocrit, INR(PT), MCHC, MCV, Platelet Count, PT, PTT, RDW, Red Blood Cells
Labs and Comorbidity	Labs + Elixhauser
Combined	All Above Features

Figure 2. List of features extracted for MIMIC III database against AMI cases

4. Results

This study employed classical ML algorithms: 1) Logistic Regression (LR), 2) Decision Tree (DT), 3) Random Forest (RF), 4) Support Vector Machine (SVM), and one deep neural network algorithm - Multi-Layer Perceptron (MLP). Python version 3.8 was used for the implementation of algorithms through Anaconda Suite. Jupiter IDE was used for coding. Various sci-kit-learn libraries were used for implementation, results generation, and feature extraction. The algorithms were implemented on the datasets individually and then on all combined. The results of these implementations are shown in Table 2. The highest accuracy, RF, achieved 92% with an AUC of 0.98.

Table 2. Summary of AUC Values for Different Datasets and Machine Learning Algorithms

Datasets	Random Forest	Logistic Regression	Support-Vector Machine	Multilayer Perceptron	Decision Tree
Combined	0.98	0.91	0.93	0.95	0.89
Admissions	0.91	0.81	0.84	0.89	0.90
Demographics	0.66	0.58	0.59	0.65	0.68
Labs	0.97	0.88	0.90	0.94	0.85
Labs + Comorbidity	0.96	0.88	0.90	0.94	0.83

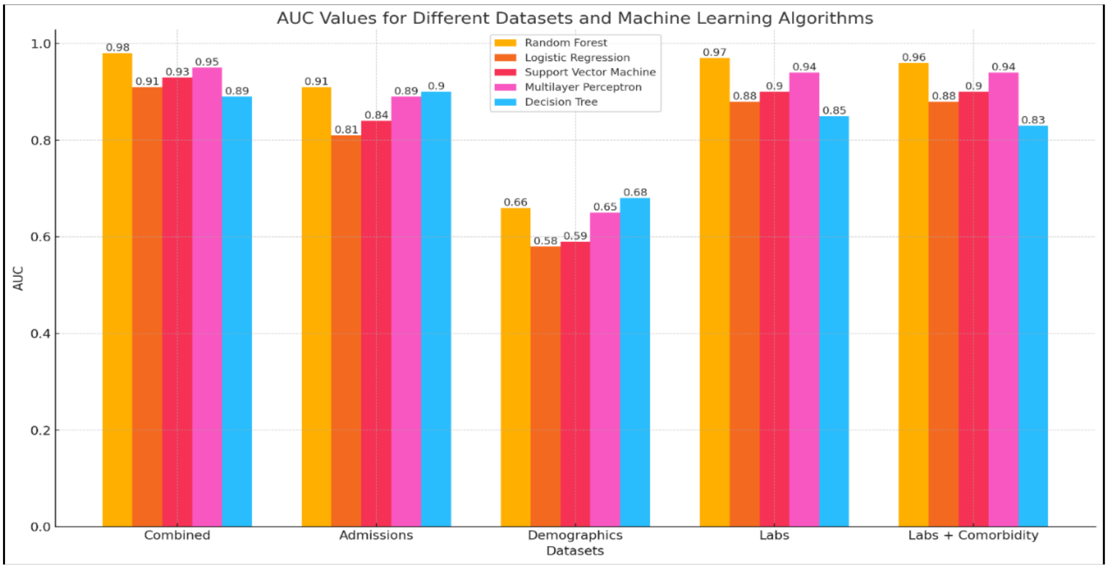

Figure 3. AUC Values for Different Dataset and Machine Learning Algorithms

Given a confusion matrix, precision is calculated by TP/ (TP+FP), and recall is given by TP/ (TP+FN). Here, TP is confirmed positive, FP is false positive, and FN is false negative. True positives are cases that were positives predicted as positives by the algorithm, FP is negative cases mispredicted as positives, and FN is a positive case mispredicted as negatives [26]. Another value, true negatives (TN), as given in the confusion matrix in Figure 2, are negative cases predicted accurately. This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, and the experimental conclusions that can be drawn.

The evaluation parameters were F1-measure, AUC, recall, and precision, detailed in Table 3. RF achieved the highest AUC value. This was closely followed by the deep neural network algorithm MLP, which achieved an AUC of 0.95. Implementation of SVM yields an AUC of 0.93, and implementation of LR yields an AUC of 0.91, whereas the AUC of DT is at least 0.89. The AUCs achieved by different datasets for all algorithms are given in Table 3. The combined dataset achieved the highest AUC value of 0.98. This was closely followed by the Lab's dataset, which achieved an AUC of 0.97. The Labs + Comorbidity dataset yields an AUC of 0.96, and the Admissions dataset yields an AUC of 0.91, whereas the AUC of the Demographics dataset is at least 0.68. All machine learning models have been validated by 10-fold cross-validation. AUC curves for all five implemented algorithms are given in Figure 3. These measures are widely used to present binary decision problems in machine learning [25].

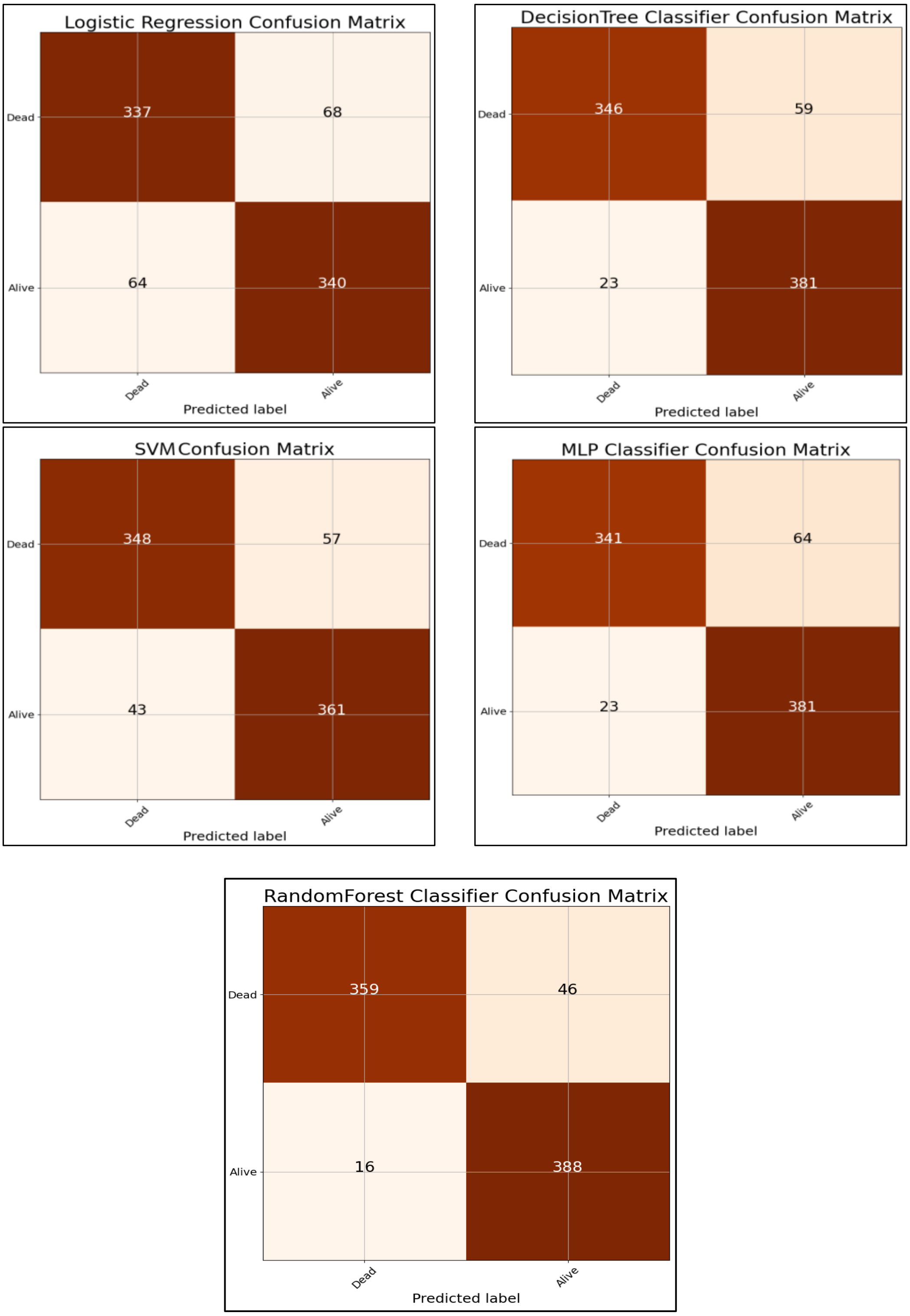

Figure 4. Confusion Matrix

Table 3. Performance metrics of machine learning models

Model	Accuracy	AUC	Precision	Recall	F1-score	Confusion Matrix
Random Forest	0.92	0.98	0.93	0.92	0.92	[[4, 1], [0, 5]]

Logistic Regression	0.84	0.91	0.84	0.84	0.84	[[5, 0], [0, 5]]
Support Vector Machine	0.88	0.93	0.88	0.88	0.88	[[5, 0], [0, 5]]
Multilayer Perceptron	0.89	0.95	0.90	0.89	0.89	[[1, 4], [0, 5]]
Decision Tree	0.90	0.89		0.90	0.90	[[5, 0], [0, 5]]

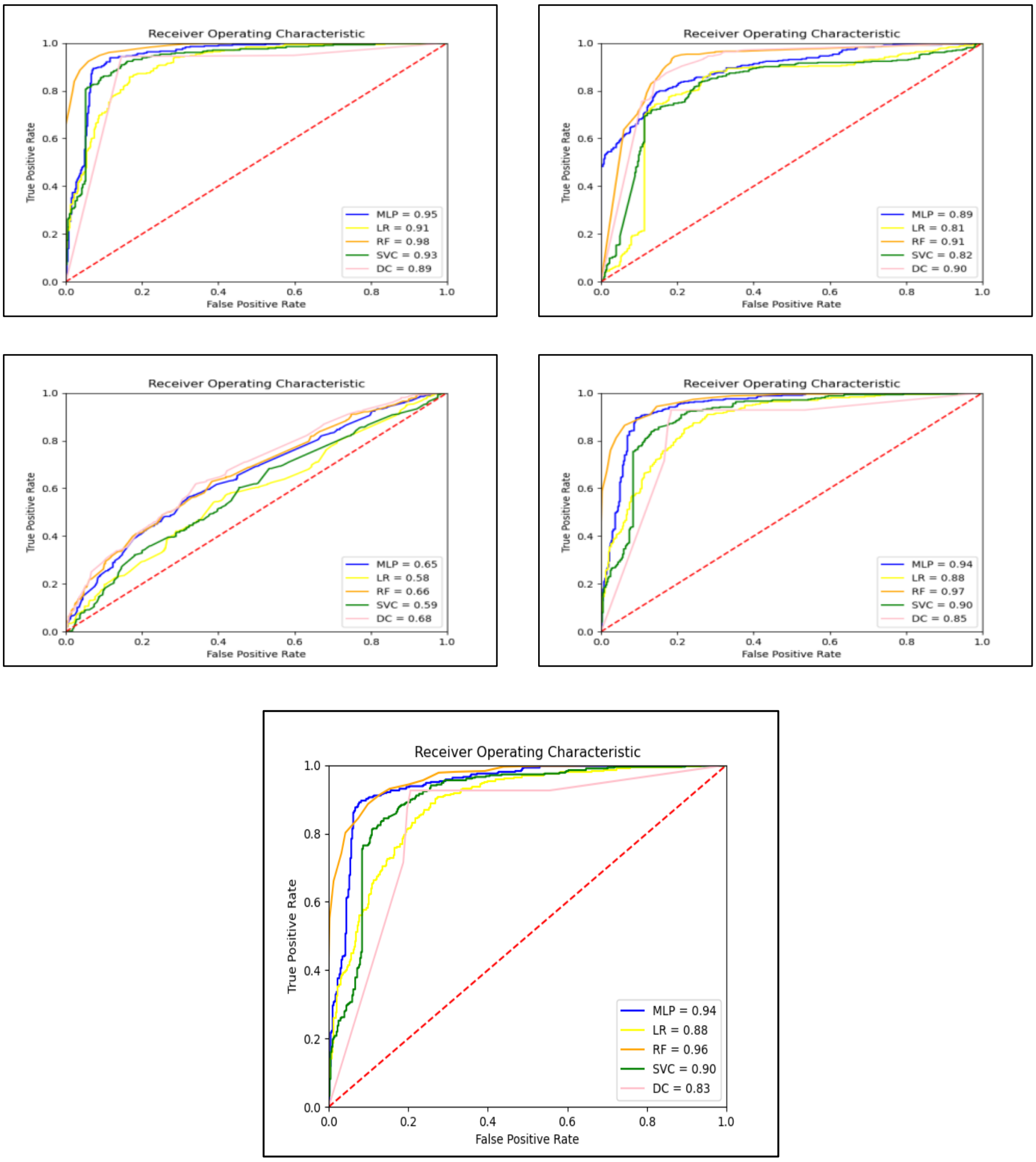

Figure 5. Combined Dataset Results

In figure 5, we have compared the AUC of our study with previous related works. As shown, this study resulted in the highest AUC along with accuracy value. Although Petrovac et al. [13] have slightly greater accuracy, the AUC for our research is far improved than any other previous work. The comparison table shows that the number of variables used for prediction is also low. This has been achieved by careful feature selection. This significantly improves the application of this study, as the majority of features are also readily available, as they are related to demographics, admission data, and routine lab results.

The provided figure 6 chart compares the performance of different machine learning models in predicting one-year mortality for patients with acute myocardial infarction (AMI). Using the Random Forest algorithm, this research paper achieved the highest Area under the Curve (AUC) value of 0.98.

Study	Topic of study	Classification Algorithm	AUC	Accuracy	# of variables
Zaheer alam. (this paper)	One-year AMI mortality prediction	Random Forest	**0.98**	92%	42
Sherazi et al. (2020) [17]	One-year mortality prediction in acute coronary syndrome	Gradient Boosting Machine/Deep Neural Network	0.898	94.7%/91.1%	69
Y. Li et al. (2020) [14]	One-year AMI mortality prediction	XGBoost	0.942	92%	59
Lee et al. (2020) [15]	One-year AMI mortality prediction	ML model (2 bootstrap decision forest models and 1 boosted tree mode)	0.918	Not mentioned	95
Salman et al. (2019) [16]	One-year AMI mortality prediction	Proposed consensus model	0.87	86.23%	Not mentioned
Payrovnaziri et al. (2019) [13]	One-year AMI mortality prediction	Deep Learning	0.916	92.89%	279
Barrett et al. (2019) [12]	One-year AMI mortality prediction	Simple Logistic/LMT	0.901	85.12%	79

Figure 6. Comparison of AUC and Accuracy to other studies

5. Discussion

Another contributing factor is the inclusion of a comorbidity index. This is significant as around 60% of patients in the dataset were not marked as having AMI as the primary reason for admission. Therefore, this suggests that AMI that occurred during admission may lead to a higher mortality rate. Hence, including a comorbidity index may contribute to accurately predicting AMI.

The results indicate that incorporating a wide range of features significantly enhances the accuracy of mortality prediction models. The Random Forest algorithm achieved the highest AUC and overall performance, demonstrating its effectiveness in handling complex datasets with multiple features.

Importance of Comprehensive Features: The combined dataset encompassing admissions, demographics, lab values, and comorbidity information resulted in the best AUC score (0.98), highlighting the necessity of including a diverse set of comprehensive features during predictive modelling.

Algorithm Performance: The Random Forest algorithm was the best, followed by the Multilayer Perceptron and Support Vector Machine with AUC of 0.95 and 0.93, respectively. Even Logistic Regression and Decision Trees (not great models) uncover some interesting patterns in the data.

Addressing Data Imbalance: Using bootstrapping and resampling techniques to balance the dataset proved effective, as evidenced by the balanced performance metrics across models. This approach minimized biases in predictions and improved the reliability of results. Clinical Relevance: Accurate mortality prediction for ICU patients with DM can greatly enhance clinical decision-making, resource allocation, and patient care. Early identification of high-risk patients allows for timely interventions, potentially reducing mortality rates and improving outcomes.

Limitations and Future Work: The study's limitations include the small sample size and the need for external validation using more extensive datasets. Future research should validate these findings with more comprehensive data and explore additional features like real-time clinical data and genetic markers to refine predictive accuracy further.

6. Conclusion

This Research demonstrates the significant potential of machine learning algorithms in predicting the mortality of ICU patients with Diabetes Mellitus. By utilizing a comprehensive dataset from the MIMIC III database, which includes admissions, demographics, lab results, and comorbidity information, we were able to build predictive models that offer valuable insights for clinical decision-making. Among the various machine learning models applied the Random Forest algorithm exhibited the highest performance, achieving an AUC of 0.98. This underscores the importance of including a wide range of features to capture the complexity of patient health status and outcomes. Other models, such as Support Vector Machine and Multilayer Perceptron, also showed strong performance, indicating their robustness and applicability in clinical settings. Integrating data balancing techniques, such as bootstrapping, effectively addressed class imbalances within the dataset, ensuring that the models could reliably predict positive and negative outcomes. This approach minimized biases and improved the overall reliability of the predictions. The findings highlight the critical role of advanced data analytics and machine learning in enhancing patient care. Accurate mortality predictions can lead to better resource allocation, timely interventions, and improved patient outcomes. The study also points to the need for continuous refinement and validation of predictive models using more significant and diverse datasets to enhance their accuracy and generalizability further.

Future research should focus on incorporating real-time clinical data and exploring additional features, such as genetic markers, to further improve the predictive power of these models. Additionally, validating these findings across different patient populations and healthcare settings will be crucial in establishing their broader applicability and effectiveness.

In conclusion, this research provides a promising step towards leveraging machine learning to improve the management and outcomes of ICU patients with Diabetes Mellitus, offering a pathway for more informed and proactive healthcare delivery.

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