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Predictive machine learning strategies and clinical diagnosis for prognosis in healthcare: Insights from MIMIC-III Dataset

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Abstract
Diagnosis prediction involves using past patient visit information to Figure out what their future health might look like which is tough but key in healthcare informatics. This work sets up a machine learning (ML) framework that can be used for clinical prognosis by learning from a database of over 40,000 anonymized MIMIC-III ICU patients. The approach requires thorough handling of the data such as missing data treatment, excluding outliers, turning categories into numbers and standardizing all the features by Z-score normalization. Highlighted features are included and the data is separated into learning and testing groups. For classification problems involving huge data sets, KNN excels which is why it is used the model reaches an accuracy of 90%, precision and recall of 92%, and an F1-score of 92%. Comparative analysis with Restreet and ULM Fit models highlights the superior performance of the proposed approach, making it a reliable and efficient tool for clinical diagnosis and prognosis in intensive care settings.

Keywords: Prognosis prediction, MIMIC-III (Medical Information Mart for Intensive Care) dataset, Machine leaning, healthcare informatics, medical classification

1. Introduction

Over the previous many years, bringing data science into healthcare has resulted in important advances in how diseases are diagnosed and estimated [1]. With the help of data-based techniques, medical staff can more successfully judge risks and respond to them in real time. In critical care, it is vital to use clinical prognosis because current data is needed to take actions that quickly affect how a patient survives and recovers [2]. Because EHRs are being used more widely, healthcare providers and researchers now have endless new data resources [3]. Equipped with information on clinical signs [4], test results and history of treatments, these datasets support the work needed to make intelligent systems that predict potential bad outcomes, use resources efficiently and improve patient care.

The largest and most common dataset employed in this area is the MIMIC-III dataset. Developed together by MIT and MIMIC-III at Beth Israel Deaconess Medical Centre maintains de-identified information for Critical units have seen the admission of more than 40,000 patients [5]. The dataset contains information such as patients' age and gender, frequent measurements of vital signs, lab results, medical codes [6], medications taken and series of heart rate and breathing rate [7]. Because MIMIC-III has records of both well-structured and informal data written by physicians [8], it covers a comprehensive range of information [9]. Because it is accessible to everyone, its use as a standard dataset helps researchers around the world share progress and hastens the improvement of matching models used in intensive care.

Researchers have used many DL and ML strategies in the past few years to explore what datasets like MIMIC-III can do [10]. These methods seek out hidden patterns and relationships in the data that aren't usually noticed by common statistics methods [11]. These models are considered good options for generating predictions related to a patient's likelihood of mortality in hospital, the total time they spend in the ICU and any risk of readmission afterwards [12].

But common challenges with clinical datasets such as lots of data elements, empty data points, noisy input and a disproportionate distribution of classes, can reduce the model's ability to succeed [13]. To solve these challenges, we rely on special data pre-processing methods, smart features selection, Principal Component Analysis (PCA) for data compression and advanced ways to improve how the model performs with new data.

A. Motivation and Contribution of the Paper: This study is motivated by the urgent need to make clinical choices in critical care simpler and more accurate, with a clear prognosis. Because patient data is growing more diverse and harder to handle in intensive care, the need for smart systems that forecast patient outcomes has grown. Standard methods of diagnosis do not always work well with the many large, high-dimensional and sometimes incomplete data sets seen in healthcare. The study uses the MIMIC-III dataset and K-Nearest Neighbours (KNN) to show that data-driven approaches can improve results prediction, limit diagnostic mistakes and guide personal treatment plans. The desire is to advance healthcare analytics and also help build models that are easy to use, adapt well and easy to understand. The report now discusses what the research added to the dataset.

- Created a reliable system for cleaning MIMIC-III data, covering handling of gaps, unusual records and turning categories into numerical values.
- Introduced feature extraction and Z-score normalization to get better accuracy by choosing the necessary data and making the input data match.
- Applied the KNN algorithm to classify patients, and it worked well for clinical datasets with several features.
- Created a thorough evaluation method by measuring parameters to determine the model's correctness and reliability, using measures include F1-score, recall, accuracy, and precision.

B. Novelty and justification of the approach: The main value of this research lies in the way both structured and unstructured data may be found in the MIMIC-III database are handled together, and through the improvement of the KNN classifier for understanding ICU patient conditions. Unlike usual methods that might ignore these points, this process starts with careful data handling, cleaning and coding, then standardizes with Z-scores to keep everything in the same range. Because KNN captures the details of complicated data patterns, it makes sense to use it in healthcare research. In addition, measuring a model with accuracy, recall, and F1-score precision allows its performance and usefulness to be checked more broadly, which is valuable for clinical use.

C. Structure of the paper: The assembly of this document is as follows: Section II outlines the field of review, Literature that explains different similar studies. Section III stated the methodology used for the research, including methods, techniques, model and performance. Section IV outlines the results and discussion of the study. Section V stated the conclusion and future approach.

2. Literature Review

This section reviews several articles on predictive ML strategies and prognostic clinical diagnosis in healthcare utilizing the MIMIC-III dataset.

Schafer and Friedrich (2019) using Fast Text and SVM with UMLS mapped thesaurus terms to word embedding models provide a foundation for automated ICD code assignment. Training data is collected from the MIMIC-III database and improved with 'is-a' linkages from the ICD-9 hierarchy. FastText is evaluated using a variety of label count estimates; one approach based on label cardinality yields an F1-score of 62.2% [14].

Zebin, Rezvy and Chaussalet (2019) confirmed their methodology with the MIMIC-III dataset after de-identification. Applying ICD-9 With regard to demographic data, the proposed Autoencoder model achieves 73.2% accuracy in differentiating between the two groups. Add vital chart event data, such as breathing and blood pressure, and body temperature, which are accessible 24 hours after admission, into the algorithm improves classification accuracy to 77.7% [15].

Fu, Yuan and Bei (2019) Work created a better cascade deep forest model for early sepsis prediction diagnostics using ML To use the new Sepsis-3 classification to categorize patients as sepsis, they extracted the patient's EMR data within the first twenty-four hours of ICU admission 3125 patients were included from the MIMIC-III dataset (1187 patients had sepsis, and 1938 patients did not). In terms of prediction performance, the enhanced cascade deep forest model is either better or comparable to other ML techniques. Their model's AUROC was zero, S0, sensitivity was 79, and specificity was 64 [16].

Nuthakki *et al*. (2019) showed how DL models outperform traditional ML models in this type of mapping. To choose, they used the most sophisticated DL approach, ULMFiT, on the biggest dataset of clinical notes from emergency departments, MIMIC III to determine the top 10 and top 50 procedure and diagnostic codes from 1.2 million clinical notes. The predictions for the top 50 ICD-9 codes for operations and diagnoses were 70.7% and 63.9%, respectively respectively, while the top 10 diagnoses and operations were predicted by their models with 80.3% and 80.5% accuracy. Unstructured clinical notes can be used to predict diagnoses and procedures, which helps human coders save time, reduce errors, and save money [17].

Yue, Ping, and Lanxin (2018) Time series containing several characteristics gathered from various sensors make up industrial data, and correct findings depend heavily on how well the features are presented. For industrial data based on DL and transfer learning, they provide a CNN-LSTM end-to-end method where CNN automatically extracts features and LSTM analyses the newly extracted feature sequences to provide precise findings. When they test their technique on the wind turbine blade icing problem dataset, they get positive outcomes when compared to previous models [18].

Kurniati *et al*. (2017) The potential of this study demonstrates the use of MIMIC-III for process mining in cancer. The MIMIC-III dataset contains sixteen event tables that might be used for process mining. The lack of readily available and easily accessible datasets with appropriate information for process mining, which has an accuracy of 89%, was a common issue in the 37 peer-reviewed articles they discovered in previous work that described process mining research in cancer. One option is publicly accessible datasets, and this study outlines the possible applications of MIMIC-III for cancer process mining. A large open access collection of de-identified medical records is called MIMIC-

III. None of the 134 articles that utilize the MIMIC dataset have made use of process mining [19].
The literature review based on clinical diagnosis for prognosis using the MIMIC-III dataset is summarized in Table I along with the methodology, dataset, results, limitations, and next steps.

Table 1: Summary of literature review based on clinical diagnosis for prognosis using MIMIC-III Dataset

Study	Methodology	Dataset	Key Findings	Limitations	Future Approach
Schafer & Friedrich (2019) [14]	SVM, FastText embeddings, UMLS mappings	MIMIC-III + ICD-9 hierarchy	FastText with label cardinality estimation achieved 62.2% F1-score for automatic ICD coding	Limited F1-score; UMLS impact not fully explored	Explore deeper embeddings, transformer-based models, and context-aware encoding
Zebin, Rezvy & Chaussalet (2019) [15]	Autoencoder + Deep Neural Network (DNN)	MIMIC-III (ICD-9 + demographics + vitals)	Accuracy increased from 73.2% to 77.7% with vital signs inclusion	Limited feature set; no real-time prediction	Incorporate real-time vitals; use temporal models like LSTM
Fu, Yuan & Bei (2019) [16]	Improved Cascade Deep Forest	MIMIC-III (EMR within 24h ICU admission)	AUROC: 0.80; Sensitivity: 79%; Specificity: 64% for Sepsis-3 classification	Moderate specificity; suboptimal AUROC	Improve preprocessing; combine with attention or temporal features
Nuthakki *et al.* (2019) [17]	DL approach using ULMFiT for code prediction from clinical notes	MIMIC-III (1.2M clinical notes)	Achieved 80.3% and 80.5% accuracy for top-10 diagnoses and procedures; 70.7% and 63.9% for top-50 ICD-9 codes	Limited to top-10 and top-50 codes; model performance decreases with more classes	Extend to full ICD code set, explore more advanced DL architectures
Yue, Ping, and Lanxin (2018) [18]	CNN for feature extraction, LSTM for sequence analysis, transfer learning	Wind turbine blade-icing + MIMIC-III	High accuracy, better than other models	Limited generalizability discussed	Apply to other sensor data, enhance interpretability
Kurniati *et al.* (2017) [19]	Process mining, literature survey	MIMIC-III	89% accuracy, highlights dataset potential	No prior use of MIMIC-III for this purpose	Implement real oncology case studies using MIMIC-III

2. Methodology

The methodology employed in this study begins with the acquisition of MIMIC-III data illustrate in Figure 1, a comprehensive clinical database comprising detailed patient records. The initial step involves data pre-processing, which includes handling missing values to maintain data integrity, eliminating outliers to reduce noise and improve model performance, and transforming categorical information into a numerical representation that ML algorithms may use by encoding them. When pre-processing is finished, the next part is feature extraction which helps pick out the features that guarantee predictive accuracy in the model. After that, Z-score normalization is done to guarantee that every feature contributes the same amount and is evaluated similarly in the analysis. Afterward, the team splits the standardized data into active subsets for modelling development and testing. Using the KNN algorithm makes sense for classification because it is straightforward and able to work with difficult data. The classifier's results are checked with the help of accuracy, precision, recall, and F1-score, offering a thorough assessment of the robustness of the classifier. The recommended procedure's sequence is shown in Figure 1. using datasets and then evaluating the results.

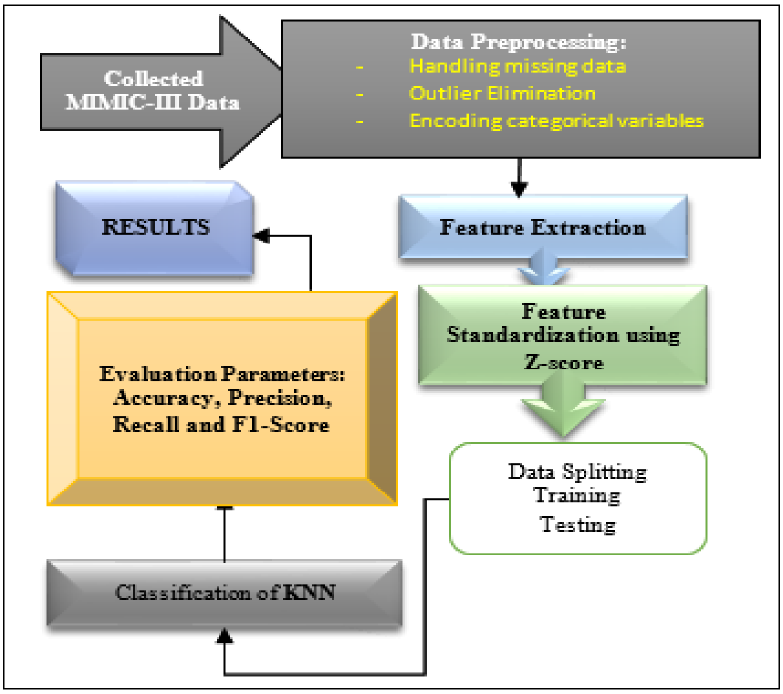

Fig 1: Data flow diagram for clinical diagnosis for prognosis in healthcare

The following steps of a data Figure 1 flow diagram are briefly explained in below:-

A. Data Collection

The MIMIC-III database was made available for public use and includes EHRs of ICU patients from data from between 2001 and 2012 was gathered at Beth Israel Deaconess Medical Centre in Boston. The database system uses 26 connected Tables of information about 58,976 adult patients who visited the hospital at one point. For the purposes of this investigation, admissions describe patient admissions and their outcomes, Patients contain their demographic details and Diagnoses_ICD and D_ICD_Diagnoses show ICD-9 diagnostic codes and their explanations, along with Noteevents and Labevents recording clinical notes and lab results.

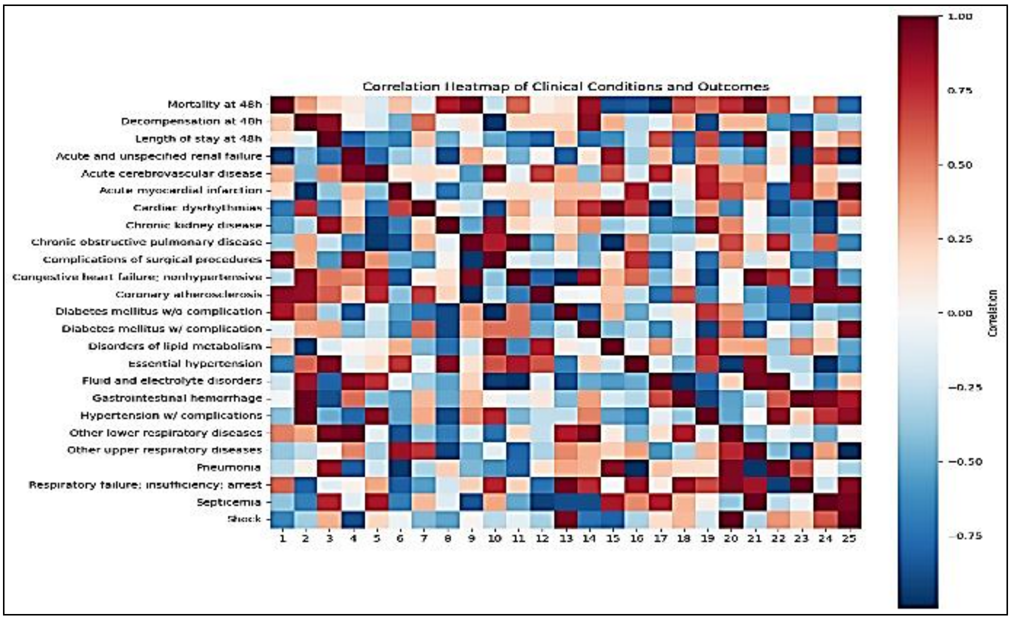

Fig 2: Correlation Matrix Heatmap

A correlation heatmap displayed in Figure 2 shows the relationships between several clinical conditions and different outcomes among ICU patients. The numbers in each of the 25x25 cells are the correlation coefficients between two medical variables, from strongest negative (blue) to strongest positive (red). The main diagonal demonstrates that a condition categorizes itself, while the cells away from the diagonal indicate relationships between conditions such as diseases and those outcomes like dying in the hospital or the period spent in the hospital. This Figure reveals common problems, co-occurring conditions and warning signs of serious problems, giving clinicians useful tips for making decisions and forecasting risks.

B. Data Preprocessing

This process involves cleaning and organizing raw data by making it ready for a more accurate model. Examples of tasks in this study include removing missing elements, reducing large data to less important features, extracting significant data, encoding labels and normalizing data. You can view the next steps in pre-processing below:

- **Handling Missing Data:** The two primary methods for handling missing data are simple deletion and filling. Items with missing values are deleted using the basic deletion procedure [20]. This approach is simple to use. When the sample has a large number of It works really well, with missing values and deleted samples making up a very small portion of the collection.
- **Outlier Elimination:** Finding and eliminating data points that substantially diverge from the dataset as a whole is part of this procedure. In this instance, individuals who have had an abnormally high number of hospitalizations.
- **Encoding Categorical Variables:** This refers to converting categorical text converting information into numerical numbers that may be processed by ML techniques. Nominal encoding is used to transform categories such as insurance type, religion, marital status, and ethnicity into unique integer values.

C. Feature Extraction

Feature extraction involves creating new meaningful variables from raw data to enhance model accuracy. In this study using the technique temporal features such as LOS and Age are extracted by calculating the difference between admission and discharge dates, and birth and admission dates respectively, capturing important patient-specific information for analysis.

D. Data Standardization with Z-Score:

The characteristics data standardization is required when the input data collection contains measurements in several units (e.g., pounds, meters, kilometres, etc.) or has considerable range inconsistencies. Standardization, often known as Z-score normalization, is a popular data standardization approach. The data points are all given the same axis using a scale where the mean equals 0 and the standard deviation equals 1. Each characteristic's data value is made the same scale as all the others by dividing its difference from the mean by the standard deviation.

$$z = \frac{value - mean}{standard\ deviation} \quad (1)$$

In the z-score normalization formula Equation (1):

z=standardized data value

$value$ = original data value

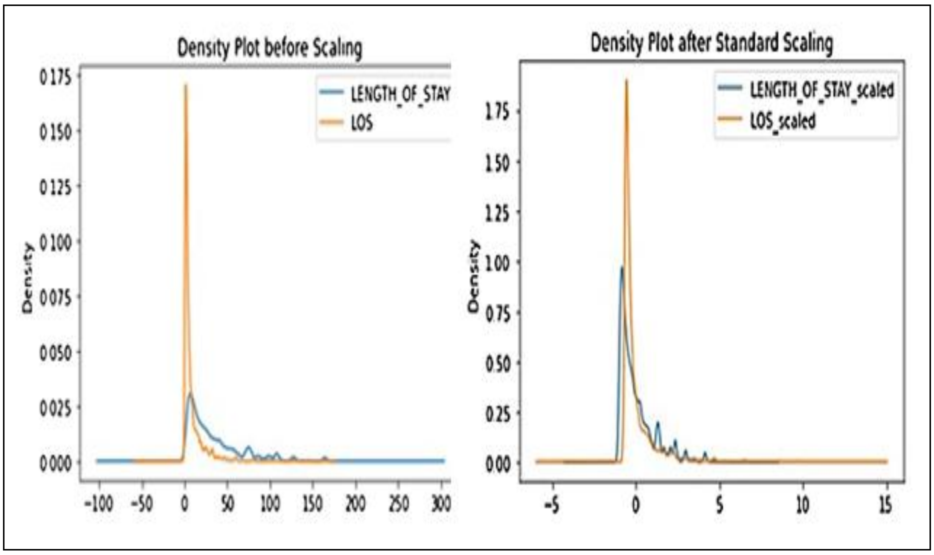

Fig 3: Density plot before and after scaling

Figure 3 illustrates before and after scaling, the LOS feature exhibits a sharp peak near 0 with a maximum density around 0.15, while Length_of_Stay has a broader, flatter distribution peaking below 0.025. The range of values is highly varied, spanning approximately from -100 to 300, indicating possible outliers and significant scale differences. After standard scaling, both features are transformed to a common scale cantered around zero, with density peaks becoming more aligned LOS _scaled reaching close to 1.8 and Length_of_Stay_ scaled peaking just under 1.0- improving comparability for ML models.

E. Data Splitting

Splitting data means training and testing the model on separate data and 80% of what we have is reserved for training, while 20% is set aside for testing.

F. Classification of KNN Model

The KNN method is a popular and simple ML methodology that employs neighbour discovery to categories a wide range real world examples of their use. The algorithm picks object values that are similar to k-class values to measure the distance between regular values and those of assaults. Initially, the system uses the chosen length to load the network data into the working area. In the training dataset, KNN looks for k-values that are much alike a particular set of values. The k-values we use are mostly from a validated classification. It’s also important to note that the input sample is categorized. Euclidean distance (Ei) was used in this investigation to determine the distances between object values. Euclidean distance is defined as shown in Equation (2):

$$E_i = \sqrt{a_1 - a_2) + (b_1 - b_2)}^2 \quad (2)$$

Where a_1, a_2, b_1, and b_2 are variables of the input data.

G. Evaluation Parameters

The performance of classification models for clinical prognosis using the MIMIC-III dataset is evaluated, which summarizes prediction results by aligning the model's outputs with the true clinical labels. The prediction model's a number of assessment metrics used to judge performance include accuracy, precision, confusion matrix, F-score and recall. Looking at a confusion matrix. This Table allows you to see how each approach predicted outcomes compared to the expected diagnosis from the patient’s medical documents. It is made up of four basic parts, which are covered below:

- **True Positive (TP):** conditions in which the model accurately forecasts whether the condition is present.
- **True Negatives (TN):** In some cases, the model predicts that the condition will not be found.
- **False Positives (FP)**: In times when the model mistakenly predicts that a certain condition exists.
- **False Negatives (FN):** Circumstances when the model is unable to identify a condition that actually exists.

Accuracy: Accuracy is the percentage of actual outcomes [21] (including true positives and true negatives) out of all the instances that were looked at. It is the main indicator of a model's general accuracy [22]. It is formulated in Equation. (3):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Precision: Precision indicates how many of the right results are out of all possible ones. It assesses how well the model predicts positive outcomes [23]. It is formally expressed as an Equation (4).

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

Recall: Recall calculates the percentage of accurately anticipated positive observations to all actual positives. Our main goal is to identify each true positive case. Not recognizing patients in high-risk groups may cause illnesses to worsen and result in a higher number of deaths shown in Equation (5):

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

F1-score: F1 score looks at both the accuracy and how precisely the test works, to determine the result. This is calculated using the equation [24]. It is calculated in Equation (6):

$$F1-Score = 2 * \frac{(Precision * Recall)}{Precision + Recall} \quad (6)$$

Experts check the efficacy of KNN models by studying matrices that tell them about the model's accuracy, precision, recall and overall results.

4. Results Analysis and Discussion

The subsequent section reviews the experimental outcomes from ML models for both diagnosis and prognosis in the MIMIC-III data collection. The study is implemented with Python in a standard Windows environment using a 64-bit system. The evaluation of the performance relies on four metrics: accuracy, recall, precision, and F1-score. The MIMIC-III dataset is used to detail the performance levels of the KNN model for clinical diagnosis and prognosis in Table II. Here, I look at the outcomes of the proposed model when using the MIMIC-III dataset.

Table 2: Performance of proposed KNN model in clinical diagnosis for prognosis using MIMIC-III Dataset

Performance Metrics	KNN
Accuracy	90
Precision	92
Recall	92
F1-Score	92

This is based on the KNN algorithm, the proposed model demonstrates good performance in all main evaluation areas, demonstrating its usefulness for classification tasks. It reaches a 90% accuracy, so the model predicts correctly for most of the cases. Besides, the model shows a precision and recall rate of 92%, showing how well it controls both unwanted positives and negatives. Having a F1-score of 92%, the model does well and remains strong across cases involving uneven data distribution. All these results prove that the KNN-based model is dependable and efficient for classifying reliably.

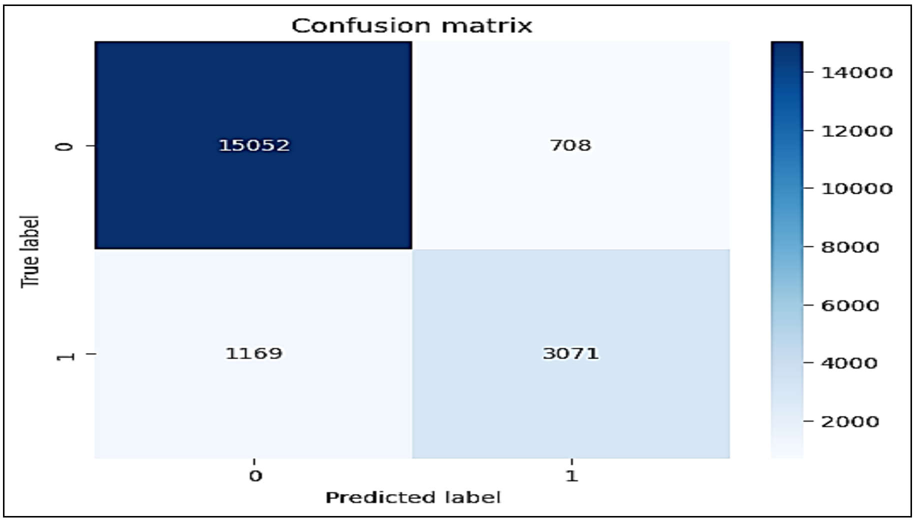

Fig 4: Confusion Matrix of KNN Model

Figure 4 serves to illustrate how a binary classification model performs. For all the normal or benign cases that were labelled as class 0, the model correctly predicted 15,052 and incorrectly classified 708 as part of class 1. Conversely, for instances truly belonging to class 1 (malicious or attack), 3,071 were correctly predicted (true positives), and 1,169 were incorrectly predicted as class 0 (false negatives). This matrix shows a comparatively low number of misclassifications and a respectable strong classification performance, particularly in identifying both classes. A greater frequency of accurate predictions is shown by the deeper hues along the diagonal.

A. Comparative Analysis

The comparative analysis of the ML model's accuracies with the proposed model in Clinical Diagnosis for Prognosis using MIMIC-III Data are provided in this section. The suggested model's strength is its ability to accurately calculate the risk factor associated with a correlation of predictors for a specific set of MIMIC-III datasets. The conventional ML method of KNN has been the research result of the suggested system. The comparison of ML models such as REPTree [25], and ULMFit [17] based on performance matrix like accuracy, precision, recall, and f1-score is illustrated in Table III.

Table 3: Comparative analysis of the ml model' with the proposed and existing model using MIMIC-III Data

Metrics	REPTree [25]	ULMFiT [17]	KNN
Accuracy	74.48	80	90
Precision	67	67	92
Recall	53	67	92
F1-Score	59	66	92

The comparative analysis of Restreet, ULM Fit, and KNN models reveals significant differences in performance across a range of assessment indicators shown in Table 3. KNN outperforms both Restreet and ULM Fit, achieving the maximum accuracy 90%, precision 92%, recall 92%, and F1-score 92%, indicating strong overall classification capability and consistency. ULM Fit, a deep learning-based the accuracy of the language model is mostly moderate 80% and well-adjusted recall and precision (both 67%), suggesting it is effective but not optimal for this task. In contrast, Restreet, a traditional ML algorithm, lags with the lowest accuracy of 74.48% and recall 53%, reflecting weaker performance, particularly in identifying positive cases. Overall, KNN demonstrates superior predictive power, while Restreet offers interpretability at the cost of lower effectiveness.

The proposed model demonstrates a significant advantage by combining high accuracy with balanced precision and recall, ensuring reliable and consistent performance across different evaluation metrics. The method proposed in this paper is superior to both Restreet, which has low recall and ULMFiT, which requires lengthy data processing and lots of computer resources. With an excellent F1-score, this model can handle both false positive and false negative cases, which is vital for use in real-life scenarios when precision and recall matter.

5. Conclusion

To design a novel way of predicting criticality using the data in the MIMIC-III data set. The adoption of analytics and modern computers in healthcare is raising the quality of predictions about patient health. The KNN algorithm is effective for making both diagnosis and prognosis with the MIMIC-III data. The act of preparing data systematically, feature extraction and model evaluation allow the proposed method to achieve high accuracy scores, for example 90%. An additional comparison confirms that KNN is more dependable and consistent than both REPTree and ULMFiT. The results support the claim that KNN is useful for processing complex medical records and can assist decision-making in important hospital settings. The fact that clinical datasets are often class imbalanced can limit how well the model performs and affects how easily it transfers its results. Depending only on simple features, current systems do not sufficiently handle changes in patient data over time.

In the future, adding different types of advanced ML approaches such as ensemble learning and structures of DL, might help the prediction accuracy even more. Experimenting with LSTM networks can help to better take care of medical data collected over time. Hybrid sampling and using explain ability techniques will play a key role in guaranteeing trust and openness in clinical use. If systems can learn and update quickly based on ongoing data, they could greatly help improve prognosis tools used in the intensive care unit.

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