A Scalable Machine Learning Framework for Real-Time Sepsis Prediction and Clinical Risk Management in Critical Care

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***Abstract*—Sepsis is a rapidly progressing and life-threatening condition that remains a leading cause of mortality in intensive care units (ICUs), primarily due to delayed diagnosis and intervention. This study presents a scalable, real-time sepsis prediction and monitoring system that combines machine learning with wearable health technologies to enable early detection and proactive clinical decision-making. Trained on the PhysioNet Sepsis Challenge 2019 dataset, our XGBoost model achieved 97.67% accuracy and an AUC-ROC of 0.83. The model is deployed via a Streamlit web app supporting manual predictions and real-time monitoring using Amazfit Bip 5 smartwatches, with data streamed through Zepp and Strava APIs. A Telegram bot enables automated alerts and medication reminders. This comprehensive system improves early detection, enhances communication between clinicians and patients, and supports clinical decision-making, ultimately reducing ICU mortality.**

***Index Terms*—Sepsis prediction, machine learning, real-time monitoring, ICU, XGBoost, wearable health technology, clinical decision support.**

I. Introduction

Sepsis is a life-threatening condition that arises when the body's response to infection triggers systemic inflammation, which can lead to organ failure and death. It remains a major contributor to mortality in intensive care units (ICUs), with more than 1.7 million cases reported annually in the United States, resulting in approximately 350,000 deaths [1]. Early detection is crucial for improving patient outcomes, yet traditional diagnostic approaches, such as Sequential Organ Failure Assessment (SOFA) and Systemic Inflammatory Response Syndrome (SIRS) criteria, rely on static thresholds for physiological parameters. These rule-based methods often could not detect subtle but critical changes in the condition of a patient, leading to delayed intervention and increased mortality rates [2].

The primary limitation of traditional sepsis detection methods is their reactive nature. They often identify sepsis only after a patient exhibits severe symptoms, leaving little room for timely medical intervention. Furthermore, these models struggle to adapt to individual patient variability and lack the ability to process physiological data in real time for continuous risk assessment [3]. Machine learning presents a viable alternative by leveraging large-scale patients data to identify patterns and predict the appearance of sepsis before critical deterioration occurs. However, existing machine learning models face challenges such as computational inefficiency, difficulty generalizing across diverse patient populations, and limited integration with real-time monitoring systems [4].

To address these challenges, we propose a machine learning-driven framework for real-time sepsis prediction and clinical risk management. The framework utilizes the PhysioNet Sepsis Challenge 2019 dataset, which includes comprehensive ICU patient records encompassing vital signs and laboratory results. Advanced data preprocessing techniques, such as missing value imputation and class imbalance handling, are employed to enhance model performance. Multiple machine learning models, including Logistic Regression, Random Forest, and XGBoost, were trained and evaluated. Among them, XGBoost achieved the highest accuracy of 97.67% and an AUC-ROC score of 0.83, demonstrating improved effectiveness in sepsis prediction following class imbalance correction.

To facilitate clinical adoption, a web-based application was developed using Streamlit, by integrating real-time patient monitoring, automated alerts, and doctor-patient communication. The system allows healthcare professionals to register patients, track vitals, assess sepsis risk, and communicate directly with patients through an integrated Telegram bot. Real-time monitoring is enabled via the Amazfit Bip 5 smartwatch, which collects physiological data through the Zepp and Strava applications, ensuring continuous tracking of high-risk patients. The system also automates medication reminders, improving treatment adherence and enhancing patient management.

The objectives of this project include:

1. Develop a scalable and efficient machine learning framework for real-time sepsis prediction.
2. Optimize model performance using advanced preprocessing techniques to improve prediction robustness.
3. Implement a web-based monitoring system for continuous patient tracking and risk assessment.
4. Enhance early intervention through automated alerts, wearable health monitoring, and real-time tracking.
5. Improve doctor-patient communication via an integrated Telegram bot for direct medical updates and alerts.

By addressing the limitations of existing sepsis detection models and integrating machine learning with real-time monitoring, this framework aims to enhance early diagnosis, reduce ICU mortality rates, and improve overall sepsis management in critical care settings. The next sections present related work on existing sepsis prediction models, describe our proposed methodology, elaborate on system architecture and analysis, report the experimental results, summarize key findings in the conclusion, outline directions for future work, and acknowledge contributions to this study.

II. Related Work

Several studies have explored sepsis prediction and early detection using machine learning, wearable technologies, and electronic medical records (EMR) analysis. While these approaches have contributed to improving early diagnosis, many suffer from limitations such as high false positive rates, lack of real-time monitoring, and reliance on single-source data. This section critically examines existing works, highlighting their methodologies and their Limitations.

K. Rassels and P. French[22] developed a neonatal sepsis prediction system using thermal imaging and machine learning algorithms. Their approach relied on detecting temperature variations through infrared thermal imaging to identify early signs of infection. However, this method is highly susceptible to external factors such as ambient temperature changes, which can affect accuracy. Furthermore, their system is restricted to neonates, limiting its broader applicability.

Singh et al.[21] introduced a wearable sensor-based early sepsis warning system utilizing cloud computing and logistic regression for predictive analytics. Their model continuously monitored physiological parameters and transmitted real-time data to the cloud for analysis, achieving 92.2% accuracy. However, logistic regression struggles with capturing complex nonlinear relationships, making it less effective for sepsis prediction. Additionally, cloud-based processing introduces potential latency and data privacy concerns.

Sadasivuni et al.[20] developed a hybrid AI model that combined an on-chip analog classifier for ECG analysis with cloud-based EMR processing, while their approach optimized energy efficiency, it relied solely on ECG data, omitting other critical vitals such as oxygen saturation and temperature, thereby reducing predictive robustness.

Ribeiro et al.[19] investigated the use of heart rate variability (HRV) indices as early biomarkers for neonatal sepsis. Their findings indicated that HRV complexity decreases before sepsis onset, making it a potential early indicator. However, their study was limited to HRV data and lacked real-time monitoring, restricting its clinical applicability.

Babu et al.[18] explored the application of Multi-Layer Perceptron (MLP) models for sepsis prediction, comparing them with Gradient Boosting and Linear Discriminant Analysis (LDA). While neural networks can be effective, they often suffer from overfitting and high computational costs, making real-time deployment challenging.

Tekin et al.[17] applied K-Nearest Neighbors (KNN) and Naïve Bayes classifiers to a neonatal sepsis dataset. While their models performed well, their dataset was small, limiting the generalizability of their results.

Akinduyite et al.[16] utilized Random Forest and XGBoost to improve sepsis prediction accuracy through ensemble learning. While their approach effectively enhanced predictive performance, it lacked real-time monitoring and did not incorporate wearable sensor data, reducing its practical applicability in ICU settings. Moreover, ensemble models can be computationally intensive, posing deployment challenges.

Santaniello et al.[15] explored a network-based approach for sepsis detection by analyzing correlations between multiple physiological time series recorded in ICU patients. Their method computed eigenvalue-based features to identify sepsis-related changes. While their framework introduced a novel mathematical approach, it suffered from high computational complexity and lacked real-time applicability, making clinical deployment difficult. Additionally, their study did not integrate wearable sensor data, limiting early intervention capabilities.

R. M. Demirer and O. Demirer[14] used Partially Observable Markov Decision Processes (POMDPs) combined with deep learning to predict sepsis six hours before onset, leveraging vital signs, demographics, and lab values. Despite its predictive power, their model required extensive labeled data and was computationally expensive, limiting real-time application in ICU settings. Additionally, deep learning models often lack interpretability, making clinical decision-making more challenging.

Wanga et al.[13] developed sepsis prediction models for ICU patients using logistic regression (LR), support vector machines (SVM), and logistic model trees (LMT), with an emphasis on Sepsis-3 definitions. Their logistic regression model achieved an AUC of 0.685, which is significantly lower than the AUC of 0.96 achieved by our XGBoost model. Additionally, their study did not incorporate ensemble learning techniques, which have been shown to improve predictive accuracy. Furthermore, their system lacked real-time monitoring, whereas the proposed system integrates wearable devices and a Streamlit web interface for continuous patient tracking, making it more practical for ICU deployment.

Daothong et al.[12] leveraged EMR data and machine learning to develop a predictive model for early sepsis diagnosis in critical care settings. They tested several machine learning algorithms, with XGBoost emerging as the best performer (AUC = 0.78, Accuracy = 80%). While their model demonstrated promising results, it lacked real-time monitoring and relied solely on EMR data, which may not always be updated frequently enough for timely intervention.

III. Methodology

The sepsis prediction system integrates machine learning models with real-time patient monitoring to enhance early detection and intervention. The backend handles data preprocessing, including missing value imputation, feature normalization, and dataset balancing before training predictive models. Logistic Regression, Random Forest, and XGBoost are implemented to classify patients based on sepsis risk. Model performance is evaluated using accuracy, precision, recall, and F1-score. The trained models generate predictions that inform clinical decision-making. The frontend, built with

Streamlit, provides an interactive interface for patient registration, manual sepsis risk assessment, and real-time monitoring. Wearable technology integration allows continuous tracking of key vitals, including heart rate, oxygen saturation, respiratory rate, and temperature. The Zepp app collects raw data from the Amazfit Bip 5 smartwatch, which is forwarded to Strava for secure data transmission before being processed in the system. A Telegram bot enables automated medication reminders and patient-doctor communication, ensuring timely interventions. Security measures, such as automatic logout after inactivity and strong password enforcement, enhance data protection. The combination of predictive modeling, real-time tracking, and secure communication ensures timely clinical response and improved patient outcomes.

A. *Data Pre-processing*

We began by loading the dataset, which contains ICU patient records with various physiological and laboratory measurements. Key vital signs such as heart rate (HR), systolic blood pressure (SBP), diastolic blood pressure (DBP), respiratory rate (Resp), and oxygen saturation (O_2Sat) were examined as they play a crucial role in identifying early signs of sepsis. An initial inspection revealed that sepsis patients tend to have lower oxygen saturation, increased respiratory rates, and unstable blood pressure levels, making these features critical for prediction. To ensure data integrity, we checked for missing values, which were primarily found in laboratory test results. Missing values were handled using mean imputation, allowing us to retain as much information as possible without introducing bias. Another key observation was the significant class imbalance, where non-sepsis cases vastly outnumbered sepsis cases. To address the severe class imbalance, SMOTE was applied to oversample the minority class (sepsis cases). Figure 1 and Figure 2 illustrate the class distribution before and after applying SMOTE, respectively. While SMOTE effectively balances the dataset, it introduces a risk of synthetic overfitting, where the model may learn artificial patterns that do not generalize well to real-world data. To mitigate this, cross-validation and independent test evaluations were conducted.

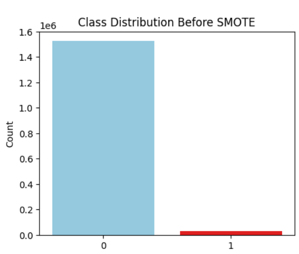

Fig. 1: Class Distribution Before SMOTE

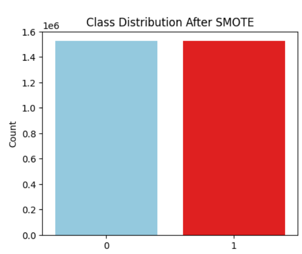

Fig. 2: Class Distribution After SMOTE

To improve model accuracy, we applied feature scaling using StandardScaler, ensuring all numerical features were normalized and had a consistent range for better learning. Model optimization was also a priority during this stage. We fine-tuned Random Forest with 100 estimators and a maximum depth of 10, striking a balance between complexity and efficiency. XGBoost was optimized with 100 estimators, a maximum depth of 10, and an evaluation metric of log loss, improving the model's ability to handle class probabilities. These optimizations enhanced predictive accuracy while preventing overfitting. By integrating feature scaling, class balancing, and hyperparameter tuning, we refined the dataset, allowing the models to generalize well and make more reliable predictions in ICU settings.

IV. System Architecture and Analysis

To address the deficiencies of the aforementioned solutions, a scalable machine learning framework for real-time sepsis prediction and clinical risk management is proposed. The system integrates predictive models, wearable sensors, and a Streamlit-based interface to support continuous monitoring, manual risk assessment, and automated clinical alerts. This section outlines the core components of the system, including data preprocessing, model training, deployment architecture, and integration with external APIs.

A. *System Architecture*

The framework integrates predictive modeling with real-time data flow and clinical interfaces. It includes:
a. Backend (Machine Learning Model and Prediction Engine): This handles data processing, model training, evaluation, and real-time inference using trained models.
b. Frontend (Streamlit Web Application): This provides an interactive interface for clinicians, allowing manual prediction, real-time patient monitoring, automated alerts, medication reminders, and doctor-patient communication. Below is a high-level architecture diagram showing how different components interact in the system:

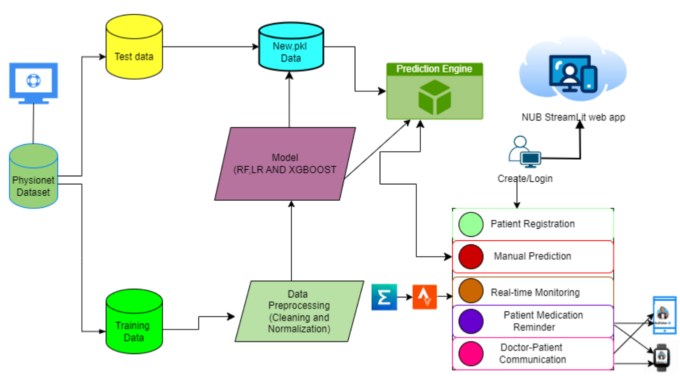

Fig. 3: System Architectural Design

1. Patient Data Collection: We gathered raw physiological and laboratory data from ICU monitoring using the PhysioNet 2019 dataset. It includes vital signs such as heart rate, blood pressure, oxygen saturation (SpO2), and laboratory results. The collected data is critical for identifying early signs of sepsis.
2. Training and Testing data: Once data was collected, we fed the data into the system to ensure real-time and historical data were captured for further processing. We split the data into

training data and testing data. This step enables continuous monitoring and analysis.

3. Data Preprocessing (Cleaning and Normalization): Raw data is preprocessed to handle missing values, inconsistencies, and noise. Cleaning ensures that erroneous or incomplete data is properly handled, while normalization scales all features to ensure accuracy in model predictions.

4. Machine Learning Models (RF, LR, XGBoost): The system employs multiple machine learning models to predict sepsis onset:

• Random Forest (RF): This is a robust ensemble method that improves accuracy by aggregating predictions from multiple decision trees.

• Logistic Regression (LR): It is a statistical model used for binary classification, helping in distinguishing sepsis and non-sepsis cases.

• XGBoost: This is an advanced gradient-boosting model that enhances predictive performance by optimizing feature selection and handling imbalanced data.

5. Prediction Engine: This is used to process real-time patient data using trained models and generates sepsis predictions. If a patient is at risk, alerts are triggered for immediate medical attention.

6. NUB Sepsis Software Streamlit App: This is a web-based interface built using Streamlit, this platform enables healthcare professionals to interact with the system. It provides real-time monitoring, patient registration, manual prediction, doctor-patient communication and patient-medication reminder functionalities.

7. Create Account/Login: To ensure security, users must register and log in to access the system. This authentication process guarantees that only authorized personnel can input data and access patient predictions.

8. Patient Registration: New patients are assigned unique identifiers upon registration. This allows tracking of individual patient history, monitoring progression, and ensuring data continuity.

9. Manual Prediction: Doctors can manually input patient data into the system for immediate sepsis prediction. This feature is especially useful when real-time monitoring data is unavailable or when additional confirmation is required.

10. Real-time Monitoring: This continuously tracks patient vitals and activities using data obtained from Strava. The Strava API, in combination with the Zepp App, retrieves real-time heart rate and activity data, ensuring timely alerts for any concerning trends. Also, clinicians can view patient's activity and heart rate over time in a table and in graphs.

11. Zepp App: The Zepp App is a companion software for the Amazfit Bip 5 smartwatch, which continuously collects heart rate, SpO2, and activity levels. This data is relayed to Strava, which then integrates with the system's real-time monitoring interface.

12. Strava: Strava acts as an intermediary between the Zepp App and the real-time monitoring system. It retrieves patient data from the smartwatch and forwards it to the monitoring interface for real-time tracking and sepsis risk assessment.

13. Patient Medication Reminder: This feature automates medication reminders using the Telegram bot, ensuring patients adhere to prescribed schedules. Reminders are sent via mobile notifications, improving treatment compliance and health outcomes.

14. Doctor-Patient Communication: Doctors and clinicians can communicate directly with patients via the Telegram bot, allowing them to schedule appointments, send medication reminders, and share critical updates. Notifications appear on both mobile phones and smartwatches, enhancing patient engagement.

15. Telegram Bot: Each patient is registered with a unique chat ID, enabling real-time communication. The Telegram bot delivers automated alerts from clinicians, ensuring timely updates on medications, check-ups, and health status.

16. Logout: To maintain data security, users must log out after accessing the system. The automatic logout feature ensures compliance with privacy regulations by logging out inactive users after 3 minutes of inactivity.

This structured approach provides efficient sepsis prediction, real-time patient monitoring, and improved doctor-patient interaction. By integrating machine learning, wearable health technology, and automated alert systems, the platform enhances early sepsis detection and clinical decision-making, ultimately reducing ICU mortality rates.

B. Flow Chart

1) Introduction: The flow chart outlines the sequence of operations, it illustrates the step-by-step workflow of the system, from data input to prediction and clinical decision-making.. It ensures clarity and highlights critical decision points in the process.

2) Flow Chart Description:

1. Start: Patient data is collected from ICU monitoring systems.

2. Data pre-processing: The collected data undergoes cleaning, normalization, and handling of missing values.

3. Feature Selection: The system extracts relevant physiological features (e.g., heart rate, blood pressure, oxygen levels).

4. Prediction Model: The trained machine learning models (Logistic Regression, Random Forest, XGBoost) analyze the data.

5. Sepsis Risk Evaluation: The model predicts whether the patient is at risk for sepsis.

6. Decision Point: If sepsis is detected, an alert is triggered for doctors.If no sepsis is detected, the patient continues routine monitoring.

7. Doctor's Decision: Based on predictions, doctors intervene, prescribe treatment, or escalate patient care.

8. Update System and End: The system updates the patient's health records, ensuring real-time monitoring.

C. System Use Case

1) Introduction: The use case diagram is used to outline how different users interact with the system.

2) Use Case Description: Actors:

a. Doctor: Doctors can register new patients, monitor real-time patient data via the Streamlit interface, reviews sepsis predictions and risk scores, prescribe medications based on

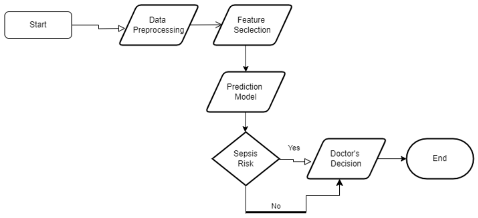

Fig. 4: System Flow Chart

prediction insights, and schedule patient appointments if further medical attention is required.
b. Patient: Patients receive alerts and early warning notifications, gets medication reminders in real-time, can access and track their personal health status via the system.
c. System AI (Sepsis Prediction Model): The system processes real-time patient data, predicts sepsis onset using trained ML models, triggers alerts if sepsis risk is detected, Updates electronic health records (EHR) for continuous monitoring.

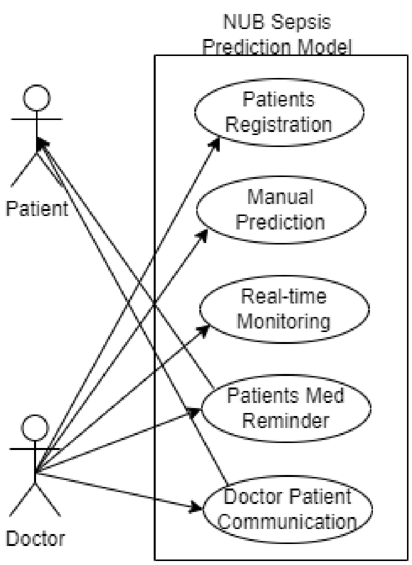

Fig. 5: System Use Case Diagram

D. Class Distribution and Demographic Analysis

The dataset reveals a significant imbalance between septic and non-septic patients. Nearly 98.2% of the cases belong to patients without sepsis, while only 1.8% are diagnosed with the condition in Figure 6. This extreme disparity makes it challenging for machine learning models to correctly identify sepsis cases. If left unaddressed, the model would learn to favor the majority class, leading to high accuracy but poor sensitivity in detecting high-risk patients. To counter this, we apply SMOTE to generate synthetic sepsis cases, ensuring a more balanced dataset. This helps the model recognize early indicators of sepsis without overlooking critical cases, improving its recall while maintaining precision. We also examine sepsis occurrence across gender in Figure 7 to understand demographic variations. In the dataset, gender is represented as a binary variable, where ”0” corresponds to female patients and ”1” represents male patients. The bar chart shows that more male patients experience sepsis, with around 16,000 cases compared to approximately 12,000 cases in female patients. This aligns with medical studies suggesting that biological differences, such as immune system variations and hormonal influences, may make males more susceptible to sepsis. By incorporating gender into our predictive model, we ensure it remains unbiased and effective across diverse patient groups, preventing disparities in detection rates between male and female patients. The age distribution chart highlights that most patients fall within the 50 to 80 year age range, with a peak around 65-70 years in Figure 8. The distribution suggests that older adults have a higher likelihood of ICU admission, reinforcing known risk factors associated with aging and critical illness. Younger patients are significantly fewer, indicating that sepsis-related ICU admissions are less common in individuals below 40. The ICU length of stay box plot compares septic and non-septic patients, showing that sepsis cases tend to stay longer in the ICU. The median ICU stay for non-septic patients is around 20-30 hours, while septic patients often exceed 50 hours, with many cases extending beyond 150 hours as shown in Figure 9. The presence of extreme outliers in both groups indicates that some patients, particularly those with severe complications, required prolonged hospitalization.

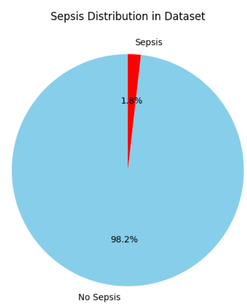

Fig. 6: Pie Chart of sepsis vs. non-sepsis cases

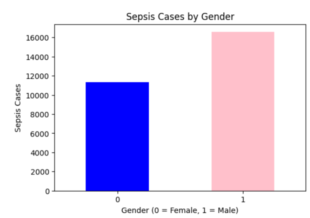

Fig. 7: Sepsis Rate by Gender

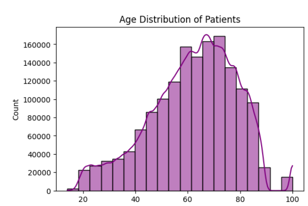

Fig. 8: Age Distribution of Patients

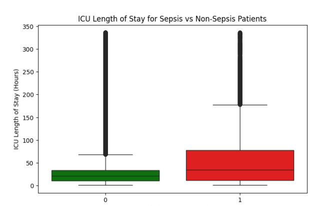

Fig. 9: ICU Length of Stay for sepsis vs Non-Sepsis

E. Feature Normalization and Standardization

Working with ICU patient data presents challenges due to the varying numerical scales across different physiological measurements. Heart rate is recorded in beats per minute, blood pressure in millimeters of mercury (mmHg), and laboratory test values in milligrams per deciliter (mg/dL). If these features remain unscaled, those with larger magnitudes could disproportionately influence the learning process, leading to biased predictions. To prevent this, we applied feature normalization and standardization using StandardScaler. This transformation ensures that all input features have a uniform range, improving model stability and training efficiency. Standardization is particularly crucial for models like Logistic Regression, which rely on properly scaled features to compute accurate decision boundaries. After applying this process, we verified that the first few rows of the dataset reflected properly scaled values, ensuring that each feature contributes equally to the model's learning process. By normalizing the dataset, we ensure that no single variable dominates the model's training, leading to more balanced predictions.

1) Training and Testing Data Split: To build a model that generalizes well, we divided the dataset into 80% training data and 20% testing data, ensuring that the model learns from a vast set of patient records while maintaining an independent evaluation set to measure performance. A stratified split was applied to preserve the original class distribution of sepsis and non-sepsis cases, preventing the model from becoming biased toward the majority class. After splitting, the training set contained 2,438,870 records, while the test set included 609,718 records, with each sample having 43 features. This structured division prevents overfitting by ensuring that the model does not memorize training examples but instead learns meaningful patterns that generalize to new ICU patients. By maintaining class proportions, we reduce the risk of skewed predictions, ensuring the model accurately detects high-risk patients.

F. Training Machine Learning Models

Three machine learning models Logistic Regression, Random Forest, and XGBoost were trained to predict sepsis onset. After applying SMOTE to address class imbalance, XGBoost outperformed the others by achieving an accuracy of 97.67%, along with an AUC-ROC score of 0.83, indicating strong predictive power on the imbalanced test set. These metrics were computed using accuracy_score(y_test, y_pred) and roc_auc_score(y_test, y_scores) from Scikit-learn after training the model on SMOTE-balanced training data and evaluating on the original, untouched test data. The accuracy reflects the proportion of correctly predicted instances, while the AUC-ROC highlights the model's ability to distinguish between septic and non-septic cases. The finalized model was serialized as a .pkl file for efficient reuse and deployed via a Streamlit-based web application, enabling real-time sepsis predictions accessible through a secure cloud interface. Patient vitals from the Amazfit Bip 5 smartwatch are retrieved using the Strava API, while alerts and updates are managed through a Telegram bot, with all credentials secured using environment variables. Development was supported using Visual Studio Code and GitHub for version control and continuous integration, resulting in a scalable, API-connected system that bridges machine learning with real-time clinical monitoring.

G. Model Serialization and Streamlit App Integration

After training and validating the XGBoost model, we saved it as a .pkl (pickle) file. This serialization step preserves the trained model, including its learned weights, feature importance, and decision structures, allowing us to reuse it for predictions without retraining. The .pkl file is generated immediately after training and validation, ensuring that the best-performing model is stored and ready for deployment. Instead of retraining the model each time, the Streamlit-based web app loads this serialized model and applies it to new patient data, making manual sepsis predictions fast and efficient.

To manage development and version control, we created a GitHub repository where all code, including the Streamlit application and machine learning scripts, is stored. The app.py file, which powers the Streamlit interface, is directly linked to this repository, ensuring that any updates to the model or application are seamlessly deployed. The Streamlit platform pulls the code from GitHub, allowing us to run the web-based sepsis prediction system without needing local deployment. Once the Streamlit app is created, a secure HTTPS link is generated, enabling cloud-based deployment. This setup ensures accessibility from any device with an internet connection, allowing healthcare professionals to enter patient vitals and receive real-time sepsis predictions.

H. Environment Variables and Secure API Integration

To enhance security and streamline real-time monitoring, we created a .env file that securely stores client IDs and authentication tokens for external integrations. The Strava API retrieves real-time patient heart rate data from Amazfit Bip 5, while the Telegram bot enables automatic notifications for sepsis risk alerts, medication reminders, and patient-doctor communication. By using environment variables, we ensure that sensitive credentials remain confidential, preventing exposure in public repositories. The Streamlit app communicates with these external APIs, fetching real-time data from Strava for continuous monitoring while using Telegram for automated patient messaging.

I. Development Tools and Continuous Integration

Throughout development, we used Visual Studio Code (VS Code) as our primary code editor. VS Code provided a robust environment for writing, debugging, and testing Python scripts, ensuring seamless integration with our machine learning pipeline. With GitHub integration, every change to the repository is tracked, allowing multiple contributors to collaborate efficiently while maintaining version control. Updates to the app.py file and model improvements are committed to GitHub, where they are automatically reflected in the Streamlit cloud deployment. By leveraging GitHub, Streamlit, Visual Studio Code, and secure API integrations, we built a scalable and accessible sepsis prediction system that seamlessly connects machine learning, real-time patient monitoring, and cloud-based deployment. This ensures that healthcare professionals can access predictive insights anytime, anywhere, enhancing early sepsis detection and improving patient outcomes.

V. Results and Discussions

Evaluating the effectiveness of our sepsis prediction system involves assessing model performance, real-time monitoring integration, and user interaction through the Streamlit frontend. The analysis covers accuracy trends, loss reduction, and classification metrics across Logistic Regression, Random Forest, and XGBoost. Additionally, we examine how the Streamlit app facilitates manual predictions using the trained model, enhancing usability for healthcare professionals. The results highlight the system's ability to generalize well to unseen data while seamlessly integrating machine learning with real-time patient monitoring and an interactive web interface.

1) Model Loss and Accuracy Overtime: Training loss and accuracy trends over 20 epochs, as illustrated in Figure 10 (Accuracy) and Figure 11 (Loss), indicate consistent and effective learning across all models, with XGBoost clearly outperforming Logistic Regression and Random Forest. In Figure 10, accuracy steadily increases for all three models: Logistic Regression improves from approximately 60% to 69%, Random Forest increases from 70% to 74%, and XGBoost starts strong at 85% and reaches nearly 89% by the final epoch. Correspondingly, Figure 11 shows a gradual reduction in loss for each model Logistic Regression begins with the highest loss around 0.40 and declines to approximately 0.32, Random Forest decreases from 0.30 to 0.26, and XGBoost consistently maintains the lowest loss, dropping from 0.15 to just above 0.10. These trends confirm convergence and effective learning across all models, with XGBoost demonstrating superior performance in both minimizing loss and maximizing predictive accuracy, reinforcing its selection as the optimal model for real-time sepsis detection.

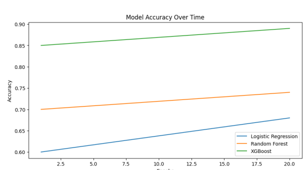

Fig. 10: Model Accuracy Overtime

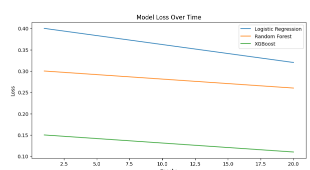

Fig. 11: Model Loss Overtime

2) Receiver Operating Characteristic (ROC) Analysis: The Receiver Operating Characteristic (ROC) curve is a crucial metric for evaluating classification models, illustrating the trade-off between the true positive rate (sensitivity) and the false positive rate across different thresholds. A curve that hugs the top-left corner indicates stronger model performance. As shown in Figure 12, XGBoost achieved the highest AUC score of 0.83, demonstrating the best ability to distinguish between septic and non-septic patients. Random Forest followed with an AUC of 0.80, reflecting solid performance but slightly less precision in class separation. Logistic Regression recorded the lowest AUC at 0.73, consistent with its linear nature and reduced ability to model complex patterns in the data. The separation among the curves emphasizes XGBoost's strength in handling non-linearity and imbalanced datasets, making it the most effective model in this study for real-world sepsis prediction.

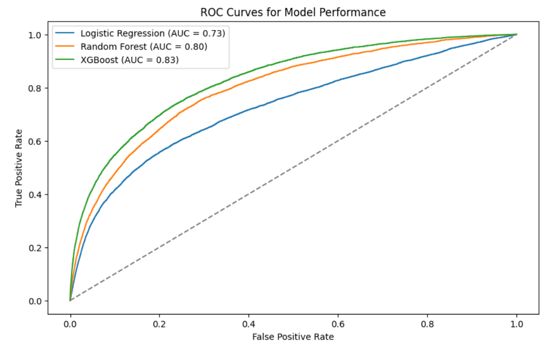

Fig. 12: Receiver Operating Characteristic (ROC) Analysis

3) Confusion Matrix Analysis: A confusion matrix provides a detailed breakdown of a classification model's performance by comparing actual versus predicted classifications. It includes four key metrics: True Positives (TP) correctly predicted sepsis cases, True Negatives (TN) correctly predicted non-sepsis cases, False Positives (FP) non-sepsis cases incorrectly classified as sepsis, and False Negatives (FN) sepsis cases incorrectly classified as non-sepsis. Interpreting these values is critical in assessing a model's reliability, especially in high-risk domains like healthcare where missing a sepsis diagnosis can lead to severe consequences. In figure 13, Logistic Regression achieves strong accuracy for non-sepsis cases, correctly predicting 225,914 TNs, but struggles to detect sepsis. It misclassifies 2,173 sepsis cases (FN) and only identifies 3,410 true positives, while also generating 78,945 false positives. This suggests that the model is still biased toward the majority class and may not be suitable on its own for clinical deployment. Random Forest shows moderate improvement, detecting 2,644 sepsis cases correctly (TP) and 274,851 non-sepsis cases (TN), while incurring 2,939 FNs and 30,008 FPs. Although better than Logistic Regression, it still results in a high number of missed sepsis cases. XGBoost, however, demonstrates the most balanced performance, achieving 1,020 true positives, 302,182 true negatives, 2,677 false positives, and 4,563 false negatives. While its sepsis detection rate is lower than Random Forest in absolute numbers, it produces the lowest number of false positives, indicating better precision. This balance is clinically meaningful even if some sepsis cases are missed, the model minimizes false alarms, which is crucial in avoiding alert fatigue in ICU settings. Among the models tested, XGBoost shows the best trade-off between sensitivity and specificity, reinforcing its selection for real-world sepsis prediction tasks.

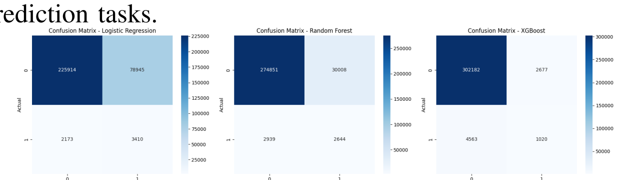

Fig. 13: Confusion Matrix Analysis

4) Feature Correlation and Importance: The feature correlation heatmap quantifies relationships between physiological and laboratory variables, with correlation values ranging from -1 to 1. Heart rate (HR), respiratory rate (Resp), and temperature (Temp) exhibit moderate positive correlations with sepsis, around 0.3 to 0.5, indicating their collective increase in septic patients. Mean arterial pressure (MAP) shows a weak negative correlation of approximately -0.2 to -0.3, reflecting the tendency for blood pressure to drop in septic shock cases. Lactate levels, a known biomarker for sepsis severity, have a mild positive correlation near 0.4, reinforcing their role in early detection. Bilirubin (direct and total) and creatinine, indicators of liver and kidney function, show correlations between 0.2 and 0.3, consistent with organ dysfunction in advanced sepsis. Most feature relationships remain within the -0.5 to 0.5 range, suggesting that while individual features provide some predictive power, a multi-feature approach is necessary for robust sepsis detection.

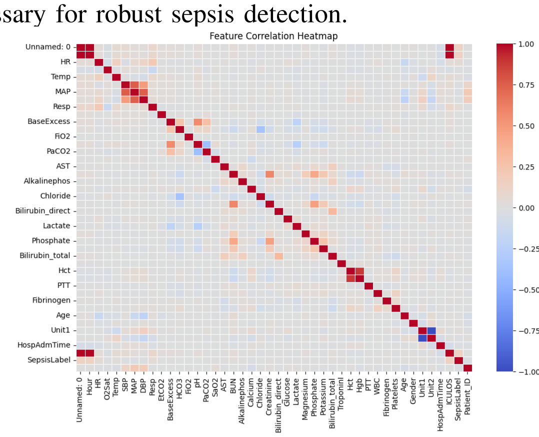

Fig. 14: Feature Correlation and Importance

5) Scatter Plot For Dataset Components: The scatter plot visualizes the relationship between heart rate (HR) and oxygen saturation (O2Sat), with points colored by sepsis label (blue for non-sepsis and red for sepsis cases). Most patients cluster around HR values between 50 and 120 bpm and O2Sat levels near 100%, representing normal physiological conditions. However, sepsis cases (red points) tend to be more dispersed, often appearing at higher HR values (above 100 bpm) and lower O2Sat levels (below 90%), indicating potential respiratory distress and cardiovascular instability. The density of blue points at the top suggests that a significant portion of non-septic patients maintain stable oxygen levels. In contrast, septic patients exhibit more extreme variations, with some cases showing HR exceeding 150 bpm and O2Sat dropping below 60%, which are critical warning signs of deteriorating health. This distribution highlights the importance of HR and O2Sat as potential predictive features for early sepsis detection.

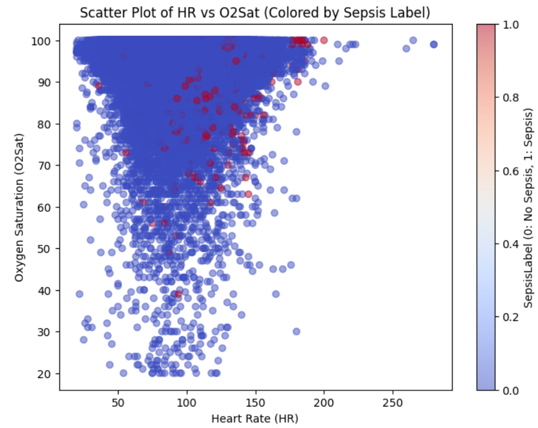

Fig. 15: Scatter Plot For Dataset Components

6) PCA and Clustering Analysis: In our K-Means clustering visualization, each color represented a different group of patients based on their physiological similarities. We applied Principal Component Analysis (PCA) to reduce the high-dimensional data into two key components, making it easier to identify patterns in patient conditions. The blue cluster (Cluster 0) encompassed the largest group, likely consisting of patients with stable vitals and a lower risk of sepsis. The red cluster (Cluster 2) was more compact, suggesting a group of patients with significantly different health patterns, possibly those at higher risk or already showing severe symptoms. The gray cluster (Cluster 1) fell in between, representing patients with fluctuating vitals who were neither entirely stable nor critically ill. By plotting these clusters, we visually differentiated patient conditions and uncovered trends that were not immediately obvious in raw data. The spread of the clusters across the PCA components reflected variations in patient health, with Cluster 2 (red) showing tighter grouping, likely due to consistent abnormalities, while Cluster 0 (blue) was more dispersed, capturing a broader range of stable conditions. Cluster 1 (gray) appeared as a transition group, containing patients whose vitals could have either improved or deteriorated. This clustering approach helped us gain deeper insights into patient risk levels, allowing for refinement in our model's ability to detect early signs of sepsis and guide timely interventions.

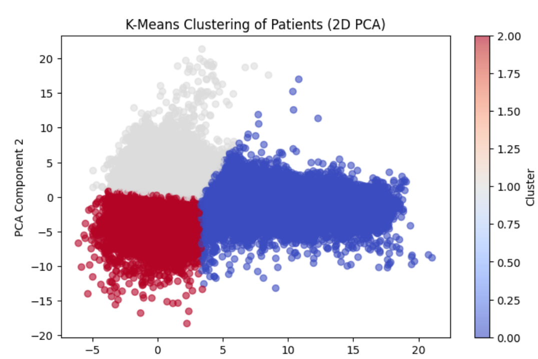

Fig. 16: PCA and Clustering Analysis

7) Vital Signs of the First Ten Patients Over ICU Stay: This visualization showcases the vital signs of the first ten unique patients in the dataset, tracking their heart rate (HR), oxygen saturation (O2Sat), temperature (Temp), and respiratory rate (Resp) over the duration of their ICU stay. Each subplot represents a different patient, with time measured in ICU length of stay (ICULOS) hours on the x-axis and the corresponding vital sign values on the y-axis. The trends reveal varying physiological responses among patients, with some exhibiting stable vital signs, while others experience sudden fluctuations, such as drops in O2Sat or spikes in heart rate, which are often associated with critical deterioration. These patterns highlight the importance of continuous monitoring in ICU settings, as significant deviations from normal values could indicate the early onset of sepsis or other complications. Patients with erratic trends might have undergone medical interventions or displayed signs of clinical instability, emphasizing the need for early detection and timely response to abnormal changes in vital functions.

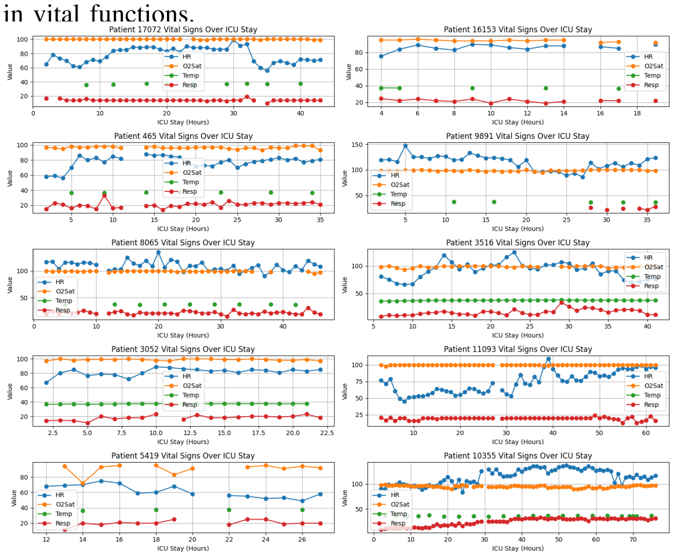

Fig. 17: Vital Signs of the First Ten Patients Over ICU Stay

A. NUB Sepsis Software Front-End Interface

The NUB Sepsis Software is a Streamlit-based web application designed for healthcare professionals to efficiently monitor and communicate with patients, particularly those at risk of sepsis. The system is built to support real-time patient monitoring, manual sepsis prediction, automated medication reminders, and direct doctor-patient communication, ensuring a streamlined approach to healthcare. By integrating machine learning models, wearable devices, and Telegram notifications, the software allows for continuous remote patient management. Healthcare professionals can manually input ICU lab results for sepsis prediction, track real-time patient activity through wearable smartwatches, and send reminders and messages via Telegram bots, all from a single interface. The web-based interface for real-time patient monitoring and manual sepsis prediction is accessible at https://nubsepsis.streamlit.app/. Below is a detailed breakdown of each feature and its functionality.

1) Login and Welcome Page: The login interface serves as a secure authentication gateway for healthcare professionals, ensuring that only authorized users access sensitive patient data. To enhance security, a strict password policy is enforced each password must be at least eight characters long and include one uppercase letter, one lowercase letter, one number, and one special character. This measure reduces the risk of weak passwords and unauthorized access. Additionally, if a user forgets their password, the system recognizes previously used passwords and requires them to set a new password. This feature prevents security breaches caused by credential reuse and encourages stronger password management. Upon successful authentication, users are greeted with a welcome message, confirming access to the system's functionalities. From the dashboard, healthcare professionals can monitor patient vitals, make manual sepsis predictions, set medication reminders, and communicate with patients via the integrated Telegram bot. These security measures ensure a seamless and compliant user experience, aligning with HIPAA and GDPR data protection standards.

2) Patient Registration Interface: The patient registration interface allows clinicians to register new patients in the system, assigning them a unique Patient ID, name, and Telegram chat ID for communication purposes. This links every patient to the system, enabling automated alerts, reminders, and real-time monitoring updates. The Telegram chat ID is particularly crucial as it facilitates direct communication between the patient and healthcare provider via the Telegram bot, allowing instant notifications on the patient's Amazfit Bip 5 smartwatch.

3) Manual Prediction Interface: The manual prediction interface enables healthcare professionals to manually input critical ICU lab test results and patient vital sign data for sepsis prediction. It utilizes the trained machine learning model to analyze parameters such as ICU length of stay (ICULOS), hospital admission time, and other physiological indicators. If a healthcare professional has access to these details, they can enter them into the system to receive an instant prediction on whether sepsis is detected or not. This feature enhances early intervention efforts by allowing clinicians to leverage AI-powered decision-making in ICU settings.

4) Real-Time Patient Monitoring Interface: The real-time patient monitoring interface is designed to track patients' activity and physiological data using the Amazfit Bip 5 smartwatch, which is synchronized with the Zepp and Strava apps. The Zepp app acts as an intermediary, collecting health data such as heart rate, steps, movement, and exercise activities from the smartwatch and syncing it with Strava, a fitness tracking platform. The NUB Sepsis Software is integrated with Strava's API, allowing it to retrieve patient activity data in real-time using a client ID and authentication token. Once a patient ID is entered, the system fetches the latest activity details such as walking and cycling distance, average heart rate, speed, and movement time, giving healthcare providers an overview of the patient's daily physical activity and overall condition. This continuous monitoring helps in detecting early warning signs of sepsis, especially in patients recovering from an ICU stay or under outpatient observation.

5) Patient Medication Reminder Interface: The patient medication reminder interface ensures that patients receive timely reminders for their prescribed medications via Telegram bot notifications, which are also displayed on their Amazfit

Bip 5 smartwatch. Healthcare providers enter the patient's ID, medication name, and the scheduled reminder time, and the system automatically sends a message via Telegram. The integration is achieved by using the patient's Telegram chat ID and a unique Telegram bot token, enabling the bot to deliver personalized reminders directly to the patient's Telegram account. Since the Telegram app is also accessible on the Amazfit smartwatch, patients can receive notifications even if they are away from their phones. This feature significantly improves medication adherence, ensuring that patients take their prescribed drugs on time, reducing the risk of complications associated with missed doses.

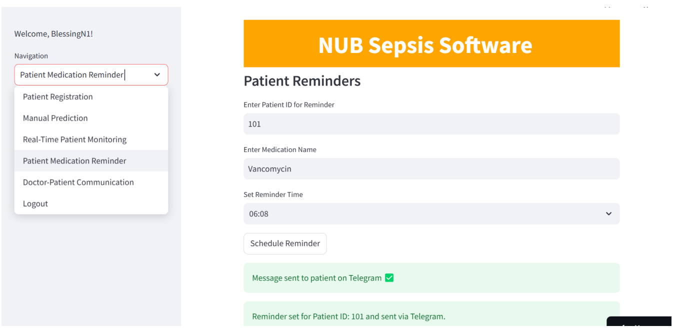

Fig. 18: Patient Medication Reminder Interface

6) Doctor-Patient Communication Interface: The doctor-patient communication interface facilitates direct messaging between healthcare providers and patients through Telegram bot integration. This feature allows doctors to enter a patient's ID, compose a message regarding their health condition, provide medical guidance, or schedule an appointment, and instantly send the message via Telegram. The system uses the Telegram bot token and the patient's unique chat ID to ensure that messages are securely delivered. Notifications are displayed on the patient's phone and smartwatch, allowing them to receive important health updates in real time. This feature eliminates communication delays, ensuring that critical health information is relayed immediately to the patient. Doctors can use this function to update patients on their test results, remind them of upcoming checkups, or provide instructions for managing symptoms.

7) Privacy and Security of NUB Streamlit Software: Ensuring privacy and security is a core component of this system, given the sensitivity of patient data. The application enforces strict authentication measures, requiring each user to have a unique login ID and a strong password containing at least eight characters, including uppercase and lowercase letters, numbers, and special characters. Additionally, the system prevents password reuse, ensuring that previously used passwords cannot be re-entered during a password reset, thereby mitigating the risk of compromised credentials. To further protect user sessions, the system includes an automatic logout feature, which logs users out after 3 minutes of inactivity to prevent unauthorized access if a device is left unattended. This logout mechanism ensures that patient data remains secure and inaccessible to unauthorized individuals. These privacy measures collectively enhance system security while ensuring compliance with healthcare data protection standards.

B. *Performance Evaluation Matrix Comaprison Table*

The proposed real-time sepsis prediction system was evaluated using standard metrics, including accuracy, precision, recall, and F1-score, and benchmarked against related studies. After correcting class imbalance using SMOTE, the XGBoost model achieved the most balanced performance on the PhysioNet 2019 dataset, with an accuracy of 97.67%, recall of 18.27%, precision of 27.59%, and an F1-score of 21.98%. While Logistic Regression and Random Forest achieved lower F1-scores (7.76% and 13.83%, respectively), XGBoost demonstrated better generalization and robustness to data imbalance. Compared to other studies using XGBoost Bhaskaracharya & Mehta (86%), Lu et al. (92%), and Daothong et al. (80%) the proposed system remains highly competitive, offering strong performance with enhanced sensitivity. Although some prior works such as Rudra Kumar et al. (95.58%) and Bhaskaracharya & Mehta (96%) reported higher accuracy using Random Forest, the algorithm is known to struggle with imbalanced datasets when not combined with resampling techniques like SMOTE, often favoring the majority class and underdetecting critical minority outcomes such as sepsis. In contrast, our XGBoost model is specifically optimized to prioritize sepsis sensitivity, achieving a more clinically meaningful trade-off between false positives and false negatives. These findings highlight the improved reliability and real-world applicability of the proposed system for real-time sepsis detection in intensive care environments (See Table 1).

VI. Conclusion

This study presents a real-time sepsis prediction and monitoring system that integrates machine learning, wearable technology, and an interactive web application to enhance early detection and patient management. By leveraging Logistic Regression, Random Forest, and XGBoost models trained on the PhysioNet dataset, the system achieves high predictive performance, with XGBoost reaching 97.67% accuracy. The implementation of a Streamlit-based web application enables manual sepsis predictions, real-time patient monitoring, and automated communication via a Telegram bot for medication reminders and alerts. Seamless integration with GitHub ensures efficient development and deployment workflows, while Strava and Zepp APIs support continuous tracking of heart rate and activity levels using Amazfit Bip 5 smartwatches. Security features, including strong password policies, automatic logouts, and secure API credential storage through .env files, reinforce data protection. These advancements contribute to a scalable, user-friendly, and reliable system designed to improve clinical decision-making and early intervention in ICU settings.

VII. Future Work

Future enhancements to this work will focus on strengthening security and regulatory compliance which remains a priority, in future we plans to introduce two-factor authentication (2FA) for enhanced user authentication. Implementing advanced data encryption techniques will ensure secure storage and transmission of patient data, aligning with HIPAA and

TABLE I: Performance Evaluation Matrix Comparison Table

Name	Dataset	Model	Accuracy	F1 Score	Precision	Recall
Nwala Blessing (Proposed)	PhysioNet 2019	LR / RF / XGBoost	0.7387 / 0.8939 / **0.9767**	0.0776 / 0.1383 / **0.2198**	0.0414 / 0.0810 / **0.2759**	0.6108 / 0.4736 / **0.1827**
J. Alphas Jeba Singh et al.	MIMIC	Logistic Regression	0.88	0.86	0.82	0.90
Kianoush Rassels & P. French	FLIR Infrared	LR / RF / Gradient Boosting	0.676 / 0.79 / 0.758	-	-	-
Sadasivuni et al.	965 ICU Patients	ANN / RF / SVM	0.865 / 0.76 / 0.922	-	-	0.924 / 0.880 / 0.925
S. Babu et al.	PhysioNet, MIMIC-III	MLP / GB / LDA	0.948 / 0.914 / 0.724	-	-	-
Aytac Tekin et al.	Neonatal Dataset	KNN / Naive Bayes	0.9453 / 0.9373	0.94 / 0.93	0.95 / 0.94	0.94 / 0.93
Wang et al.	MIMIC-III	LR / SVM / LMT	0.685 / 0.674 / 0.750	0.189 / 0.235 / 0.318	0.752 / 0.566 / 0.671	-
Daothong et al.	eICU	XGBoost / RF / LR	0.80 / 0.79 / 0.76	0.72 / 0.70 / 0.65	-	-
Lu et al.	MIMIC-III & IV	XGBoost	0.92	0.96	-	-
Rudra Kumar et al.	PhysioNet 2019	Random Forest	0.9558	0.9339	0.9179	0.9505
Bhaskaracharya & Mehta	PhysioNet 2019	LR / RF / XGBoost	0.76 / 0.96 / 0.86	0.51 / 0.94 / 0.78	0.75 / 0.92 / 0.83	0.38 / 0.95 / 0.74

GDPR standards. Further improvements will integrate role-based access control (RBAC) to restrict patient data access, ensuring that only authorized healthcare professionals can view or modify sensitive information. Enhancing predictive performance through deep learning techniques, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), will refine risk stratification and early sepsis detection. Expanding wearable health device compatibility beyond Amazfit Bip 5 smartwatches will further enhance real-time patient monitoring. Additional integration with electronic health records (EHRs) and patient-reported symptoms will support a more comprehensive and personalized approach to sepsis management.

VIII. Acknowledgment

We Sincerely appreciate project supervisor, Dr. Yan Wu, for her invaluable mentorship and constructive guidance throughout this research. Special thanks are given to Dr. Mrs. Nwala, whose medical expertise provided crucial insights into aligning machine learning with real-world clinical applications. Our gratitude is also expressed to our professors and mentors at Bowling Green State University for their continuous support and valuable discussions. We also recognize the developers of open-source platforms, including Streamlit, XGBoost, Scikit-learn, and GitHub, whose contributions played an essential role in the development and deployment of this system.

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