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RESEARCH ARTICLE

Effective Hypertension Detection Using Predictive Feature Engineering and Deep Learning

SIDRA ABBAS [1], (Graduate Student Member, IEEE), GABRIEL AVELINO SAMPEDRO [2], MOEZ KRICHEN [3,4], (Member, IEEE), MEZNAH A. ALAMRO [5], ALAEDDINE MIHOUB [6], AND RASTISLAV KULHANEK [7]

[1]Department of Computer Science, COMSATS University Islamabad, Islamabad 45550, Pakistan
[2]School of Management and Information Technology, De La Salle—College of Saint Benilde, Manila 1004, Philippines
[3]FCSIT, Al-Baha University, Al Bahah 65528, Saudi Arabia
[4]ReDCAD Laboratory, University of Sfax, Sfax 3038, Tunisia
[5]Department of Information Technology, College of Computer & Information Science, Princess Nourah Bint Abdul Rahman University, Riyadh 11564, Saudi Arabia
[6]Department of Management Information Systems and Production Management, College of Business and Economics, Qassim University, Buraydah 51452, Saudi Arabia
[7]Department of Information Management and Business Systems, Faculty of Management, Comenius University Bratislava, 82005 Bratislava, Slovakia

Corresponding authors: Rastislav Kulhanek (rastislav.kulhanek@fm.uniba.sk) and Sidra Abbas (sidraabbas@ieee.org)

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ABSTRACT The increasing occurrence of Hypertension highlights the need for advanced predictive tools in healthcare. This research proposes a novel approach that combines machine and deep learning for new feature generation and hypertension prediction. We explore machine learning-based models: Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), XGBoost (XGB), and Gradient Boosting (GB) for new Feature Prediction (FP) and integrated these predictions with the original dataset for training deep Long short-term memory (LSTM) model. To evaluate the efficiency of the proposed approach, we compare all models, predicting new features, with those in the existing study. The results demonstrate that the GB-based FP + LSTM are standout performers. The GB-based FP + LSTM combination demonstrates the highest accuracy at 98.48%. On the contrary, the LR-based FP + LSTM combination exhibits a lower accuracy of 89.39%. The remaining combinations, including RF-based FP + LSTM, XGB-based FP + LSTM, and DT-based FP + LSTM, showcase accuracies ranging from 95.45% to 97.97%. In practical terms, the high F1-score of 98.48% is achieved by the combination of GB-based FP + LSTM, which implies a reliable tool for clinicians to aid in early hypertension detection. These findings hold deep practical implications, offering healthcare practitioners and policymakers a pathway to deploy accurate and timely hypertension identification tools.

INDEX TERMS Hypertension, deep learning, machine learning, feature generation, healthcare, predictive modeling.

I. INTRODUCTION

Hypertension, commonly known as high blood pressure, represents a ubiquitous health condition with profound implications for human well-being [1], [2]. The silent and gradual onset of Hypertension often conceals its potential to wreak devastation on various physiological systems [3]. In addition, elevated blood pressure imposes a sustained burden on the heart, arteries, and other vital organs, leading to an increased risk of severe health complications such as heart attacks, strokes, kidney dysfunction, and cognitive decline [4]. The tricky nature of Hypertension, often asymptomatic until advanced stages, underscores the critical need for timely detection and intervention [5]. Likewise, detecting

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Hypertension at an early stage is not merely a matter of monitoring numerical values; rather, it is a crucial step toward preventing life-threatening outcomes. Specifically, early identification enables healthcare professionals to implement targeted interventions, ranging from lifestyle modifications to pharmacological treatments, mitigating the progression of Hypertension and reducing the risk of associated complications.

Similarly, given the substantial impact of Hypertension on human health, the imperative to develop effective detection methods is clear. Most importantly, with its capacity to analyze complex patterns in health data, machine learning emerges as a promising avenue for revolutionizing hypertension detection, potentially saving countless lives through proactive and personalized healthcare interventions [6]. However, while essential, traditional blood pressure monitoring methods often present challenges in continuous, real-time assessment, making them less than optimal for timely intervention.

Machine learning's effectiveness in detecting Hypertension lies in its ability to analyze vast and diverse datasets, extracting fine patterns and correlations that may elude traditional diagnostic approaches [7], [8]. Likewise, unlike conventional methods that rely on intermittent measurements, machine learning algorithms can process continuous physiological data streams, offering a more comprehensive and dynamic assessment of blood pressure variations [9], [10]. In addition, these algorithms can integrate information from various sources, including wearable devices, electronic health records, and lifestyle data, providing a holistic understanding of an individual's health status [11]. It is important to note that machine learning models can also adapt and evolve with emerging data, enhancing their predictive capabilities over time. More precisely, the predictive power of these algorithms, for instance, DTs and LR, is crucial in identifying subtle deviations in physiological parameters that may precede overt Hypertension, enabling early intervention and personalized healthcare strategies. Moreover, machine learning contributes to developing risk prediction models, helping healthcare professionals stratify individuals based on their likelihood of developing Hypertension, optimizing resource allocation and prioritizing preventive measures for those at higher risk. Machine learning can change hypertension detection from reactive to proactive healthcare [12], [13].

In sum, integrating machine learning algorithms in healthcare technology represents a paradigm shift in hypertension detection. Machine learning has the potential to sift through complex data sets, analyze patterns, and provide continuous monitoring, opening new avenues for early detection and personalized management of Hypertension. Subsequently, these innovative solutions promise to revolutionize traditional practices, offering a proactive approach that can significantly impact patient outcomes. The synthesis of technology and medical science enhances our understanding of Hypertension. Likewise, it propels us towards a future where timely interventions, driven by machine learning insights, can save lives and alleviate the burden of cardiovascular diseases. This paper explores the potential of machine learning in hypertension detection, emphasizing its role in healthcare practices. Overall, the collaboration between healthcare professionals and machine learning technologies stands balanced to redefine the standards of care for Hypertension and beyond.

A. CONTRIBUTIONS

This paper makes the following contributions:

- **Feature Engineering with Machine Learning Classifier:** To augment the feature set, RF, LR, DT, XGB, and GB classifiers are trained on the original features. Likewise, the predictions from this classifier are utilized as additional features, providing the machine-learning model with enhanced discriminatory power. Combining LSTM, dense layers, and dropout regularization, this architecture captures slight dependencies and improves the model's predictive performance for multi-class hypertension classification.
- **Improving Hypertension Prediction by Combining Machine Learning and Deep Learning:** This study aims to improve hypertension prediction by combining machine learning-based feature engineering and deep learning-based prediction. The study found that the combination of GB and LSTM models produced an F1-score of 98.48%. These findings provide valuable insights into the models' performance across various metrics.

B. PAPER ORGANIZATION

Section II provides the related work on hypertension. Section III outlines the research methodology for hypertension detection. Section IV provides the experimental analysis, results and discussion. Lastly, Section V concludes the work and leads to the future directions.

II. RELATED WORK

A thorough examination of existing research is instrumental in contextualizing the current landscape of hypertension detection using machine learning. Recent years have witnessed a surge in studies exploring the junction of healthcare and artificial intelligence, with a particular focus on the application of machine learning in hypertension management [14], [15]. Notable contributions include research efforts that leverage diverse datasets encompassing physiological measurements, electronic health records, and lifestyle factors [16]. Likewise, studies have explored developing and validating machine learning models capable of accurately predicting blood pressure trends [17], [18]. Concurrently, exploration of the integration of wearable devices and machine learning algorithms for continuous blood pressure monitoring showcases the potential for real-time health assessments. Similarly, Smartwatches and smartphones with wearable capabilities have been designed to measure blood pressure through photoplethysmography [19]. In addition, advancements in feature engineering techniques, model interpretability, and the utilization of deep learning architectures have spearheaded recent investigations [20]. While these works collectively underscore the promise of machine learning in hypertension detection, it is imperative to critically evaluate their methodologies, limitations, and the generalizability of their findings.

Building upon the foundation laid by previous research, several studies have investigated integrating machine learning into clinical workflows for hypertension detection. Likewise, the integration of developing a predictive model that seamlessly interfaces with electronic health records provides clinicians with real-time insights into patients' blood pressure trends [21], [22]. Furthermore, the interpretability of machine learning models addresses the often-cited challenge of understanding the decision-making process [23], [24]. The author of the paper [1] introduced ExHyptNet, an innovative deep learning system using wearable devices like smartwatches. It detects Hypertension through photoplethysmography signals. These signals get treated visually by ExHyptNet using EfficientNet, which is pre-trained for PPG analysis. Heatmaps and attention processes enhance interpretability for healthcare experts. ExHyptNet surpasses current methods with high classification accuracy in diagnosing Hypertension. Furthermore, its explainable modules clarify the underlying reasoning. Thus, ExHyptNet advances non-invasive hypertension detection significantly, aiding clinical decisions with accuracy and transparency. The suggested approach is positioned as a viable option for non-invasive continuous blood pressure monitoring using wearable technology, and the research also addresses the significance of feature selection in improving the DNN model's performance.

This author of the paper [25] suggests a revolutionary method known as "risk stratification"—a machine learning model—to identify those who are more likely to develop diabetes and Hypertension. This method allows healthcare resources to be allocated efficiently to those who need them the most. Through the collection of basic clinical test results, medical history, and demographic data from a population in a resource-constrained situation, the researchers created and assessed a number of machine learning models for risk prediction, including logistic regression and random forest. When the trained models were tested on different test datasets, they outperformed conventional risk stratification techniques in scenarios with limited resources in terms of accuracy. The model performed well and surpassed its previous competitors with a gap of 13.5%, achieving 79.2% in the limited environment. In particular, the random forest model proved to be the best, with great accuracy, in predicting the risk of Hypertension and diabetes.

In South Asia, where Hypertension is highly prevalent, the author in this paper [26] looks into the implementation of machine learning models for population-level hypertension prediction. The research uses these models to combine individual-level data from nationally representative surveys carried out in Bangladesh, Nepal, and India in order to identify important determinants linked to Hypertension. The study trains and evaluates these models on the combined dataset using a variety of machine learning algorithms, including Decision Trees (DT), Random Forests (RF), Gradient Boosting Machines (GB), Extreme Gradient Boosting (XGB), Logistic Regression (LR), and Linear Discriminant Analysis (LDA). The results reveal that machine learning models can accurately predict Hypertension with a high degree of accuracy on LDA, around 90%, with the models with the greatest performance scores being XGBoost, GBM, LR, and LDA. Overall, these advancements signify a maturation of the field, moving beyond proof-of-concept studies to practical implementations that could reshape how Hypertension is detected and managed in real-world healthcare settings.

The reviewed studies collectively highlight the potential of machine learning for hypertension detection, monitoring, and management in clinical and real-world settings. Likewise, from predictive models seamlessly integrated into electronic health records to deep learning architectures automating feature extraction, the methodologies employed reflect a dynamic and rapidly evolving field. The integration of wearable devices, feature selection techniques, and ensemble learning approaches further accentuate the multifaceted nature of recent research efforts. However, as the field progresses, it is essential to consider these machine learning applications' scalability, ethical implications, and interoperability, ensuring seamless integration into existing healthcare infrastructures. This section explores recent studies, explaining their contributions and limitations while setting the stage for a comprehensive synthesis in the subsequent sections. In conclusion, this section provides a comprehensive overview of the existing body of work, laying the groundwork for the subsequent analysis and synthesis of state-of-the-art approaches in hypertension detection through machine learning methodologies. Table 1 presents the comparison between previous techniques and the features of their dataset.

TABLE 1. **Comparison of methods and datasets.**

Models	Methods	Datasets
[1]	Deep Neural Network	Table 2 presents some of the important features used in the model training.
[25]	Random Forest Model	The variables dataset included are Age, Height, Weight, BMI, Heart rate, Random blood sugar, Waist circumference, Systolic blood pressure, Diastolic blood pressure, Urinations per night, Parental diabetes, Parental hypertension, Current smoker, Chest pain etc.
[26]	ML Models	The variables dataset included are blood pressure (BP), sociodemographic and economic factors, height, weight, hemoglobin, and random blood glucose

III. RESEARCH METHODOLOGY

This study adopts a systematic approach to predicting Hypertension using machine learning methodologies. Figure 1 outlines the steps and approach employed in this research. In this research, the proposed methodology leveraged a comprehensive health dataset designed for non-invasive cardiovascular disease detection [27]. Likewise, the dataset encompasses 657 records from 219 subjects, spanning an age range of 20 to 89 years, and includes information on prevalent conditions such as Hypertension and diabetes as shown in equation 1.

$$\begin{aligned} S &= 219 \\ R &= 657 \\ A_{\min} &= 20 \text{ years old} \\ A_{\max} &= 89 \text{ years old} \end{aligned} \tag{1}$$

In addition, data acquisition followed standardized experimental conditions, ensuring reliability. The study employed the dataset to investigate photoplethysmograph signal quality assessment thoroughly and sought to unveil the intrinsic relationship between PPG waveforms and cardiovascular diseases. This research used the latent characteristic information embedded in PPG signals for early and noninvasive screening of common CVDs, particularly Hypertension. Subsequently, the dataset underwent a detailed preprocessing phase to optimize it for subsequent analysis. Columns associated with specific health conditions, namely *Diabetes*, *Cerebral Infarction*, and *Cerebrovascular Disease*, were systematically removed from the dataset, resulting in a refined version referred to as `dfnew`. Likewise, categorical columns, such as *Sex(M/F)* and *Hypertension*, were then subjected to label encoding to transform them into numerical representations, facilitating a seamless integration of these variables into the analytical process. Following preprocessing, a comprehensive Exploratory Data Analysis was conducted to unveil the intricate relationships within the dataset. Additionally, the correlation matrix, a fundamental statistical tool, was computed to discern the strength and direction of correlations between various variables. Similarly, visualized through a heatmap, this matrix played a pivotal role in guiding feature selection for subsequent analysis, offering insights into the interplay of different health parameters. Moreover, feature selection aims to enhance the model's efficiency by focusing on the most relevant variables. Specific columns, namely *Heart Rate(b/m)*, *Height(cm)*, *subject ID*, and *Num.*, were discreetly excluded to create a final, refined dataset denoted as `dfnewfinal`. This meticulous feature curation ensures that the subsequent machine learning models are streamlined and adept at capturing the essential aspects of blood pressure prediction. In addition, a critical analysis of the distribution of the target variable. The dataset was analyzed using different feature analysis techniques, after which the dataset was shrunk to 7 features described in Table 2.

TABLE 2. Feature description.

Features	Description
Sex	Stores Gender details of the patient that help in determining the type of pressure
Age	Stores patients age that helps in determining the severity and amount of disease
Weight	Stores weight details of patient, helps in the psychology of patient
Systolic Blood Pressure	It represents the maximum blood pressure on artery walls; it indicates cardiovascular health and is utilized in clinical procedures to detect various cardiovascular conditions that include hypertension
Diastolic Blood Pressure	It represents the minimum blood pressure on artery walls and indicates cardiovascular health and is utilized in clinical procedures to detect various cardiovascular conditions including hypertension
BMI	It stands for Body Mass Index, used to measure body fatness and is connected with the risk of several health conditions including cardiovascular issues, hypertension etc.

This dataset detects Hypertension from its root cause, blood pressure; it consists of blood pressure readings, including Systolic and Diastolic Blood Pressure. BMI measures the fat stored in the body that may lead to heart issues due to high cholesterol. These are the main indicators that can help identify Hypertension in comparison to other datasets that mostly focus on diabetes, uric acid smoking details, etc. Furthermore, *Hypertension* was undertaken to address potential issues related to data imbalance. The distribution ratios for each category within the variable were quantified, shedding light on the prevalence of different hypertensive cases. Specifically, this analysis was visually represented through a count plot, providing a comprehensive overview of the distribution of hypertension cases within the dataset. The dataset was then systematically divided into two components: features (`X`) and the target variable (`y`). This division is essential for subsequent model training and evaluation, ensuring that the developed models can generalize effectively to unseen data. More precisely, filling these values with zeros was employed to handle any missing values within the dataset. This step ensures completeness in the dataset and sets the stage for a comprehensive analysis. These methodological steps, including dataset preprocessing, exploratory data analysis, feature selection, and data splitting, provide a strong foundation for subsequent phases of the study. Importantly, the curated dataset is now poised for developing, training, and evaluating machine learning models to predict blood pressure. Figure 2 provides the correlation coefficients (CC) between various dataset features. It measures the strength and direction of linear relationships between two variables. Furthermore, it shows the degree of association between each feature, with negative values indicating a negative correlation and positive values indicating a positive correlation. The CC between age and Hypertension is -0.16, which indicates a weak negative correlation. Old age is slightly associated with a lower risk of Hypertension, but this relationship is not very strong. Similarly, the CC between weight and blood pressure

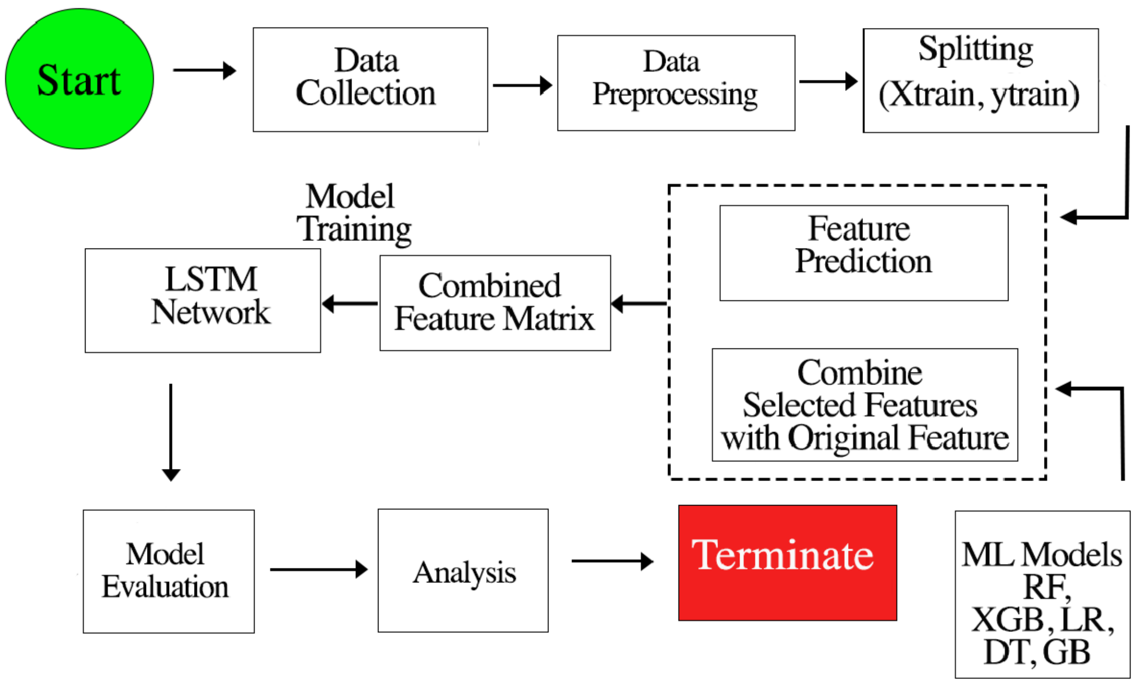


FIGURE 1. Proposed Methodology for Feature Prediction, Feature Addition, and Hypertension Prediction.

is around 0.2, indicating a weak positive correlation. Higher weight is slightly associated with higher blood pressure, but this relationship is not very strong.

A. ML MODELS WITH DL MODEL

Algorithm 1 presents an overview of the entire pipeline of the proposed approach, which begins with collecting data and preprocessing it. The results are then analyzed using evaluation metrics, and subsequently, the confusion matrix and ROC curves are extracted. This study examined machine learning models such as RF, LR, DT, XGB, and GB for Feature Prediction (FP). The predictions from these models were then combined with the original dataset and utilized for training with LSTM. Subsequently, an RF, LR, DT Classifier, XGB, and GB classifiers were employed to enhance the model's predictive capabilities. Likewise, the features were flattened, and the classifier was trained on the training set ($X_{\text{train}}, y_{\text{train}}$). Subsequently, predictions from the RF, LR, DT, XGB, and GB models were incorporated as additional features. These predictions were combined with the original feature set, and sequences were padded for input data. The resulting combined and padded sequences, $X_{\text{train\_padded}}$ and $X_{\text{test\_padded}}$, were reshaped for compatibility with a LSTM network. Subsequently, a sequential neural network model, consisting of an LSTM layer followed by densely connected layers, was defined for multi-class classification. In addition, the model architecture included an input shape corresponding to the padded sequences. Dropout regularization was introduced to prevent overfitting, and the output layer utilized the softmax activation function to facilitate multi-class classification. The model was compiled using the categorical cross-entropy loss function and the Adam optimizer. Moreover, the model was trained using the combined features with early stopping and model checkpoint callbacks. During training, the best model based on validation accuracy was saved. The training process involved 50 epochs with a batch size of 32. The best model was loaded for evaluation on the test set ($X_{\text{test\_padded}}, y_{\text{test\_categorical}}$). The selection and use of each of these techniques, namely loss functions, gradient descent, activation functions, dropout, and cross-entropy, were, of course, because they can contribute to the solution of machine learning and deep learning models for hypertension prediction. Every technique among them was selected judiciously only if it has the potential to conclude prediction errors, optimize model parameters, introduce necessary non-linearity for complex data patterns, avoid overfitting, and improve classification accuracy. These techniques, however, collectively contributed to the reliability, scalability, and interpretability of the hypertension prediction framework, which are dynamic requirements for any application in healthcare. Furthermore, model performance on the test set was evaluated using various metrics. Predictions (y_{pred}) were compared against true labels ($y_{\text{test\_true}}$), and metrics including accuracy, precision, recall, and F1-score were computed. The metrics provide a comprehensive assessment of the model's classification performance. The trained model's performance metrics, including accuracy, precision, recall, F1-score, confusion matrix, and ROC curves, were calculated and analyzed to gauge the effectiveness of the developed machine-learning model in predicting Hypertension.

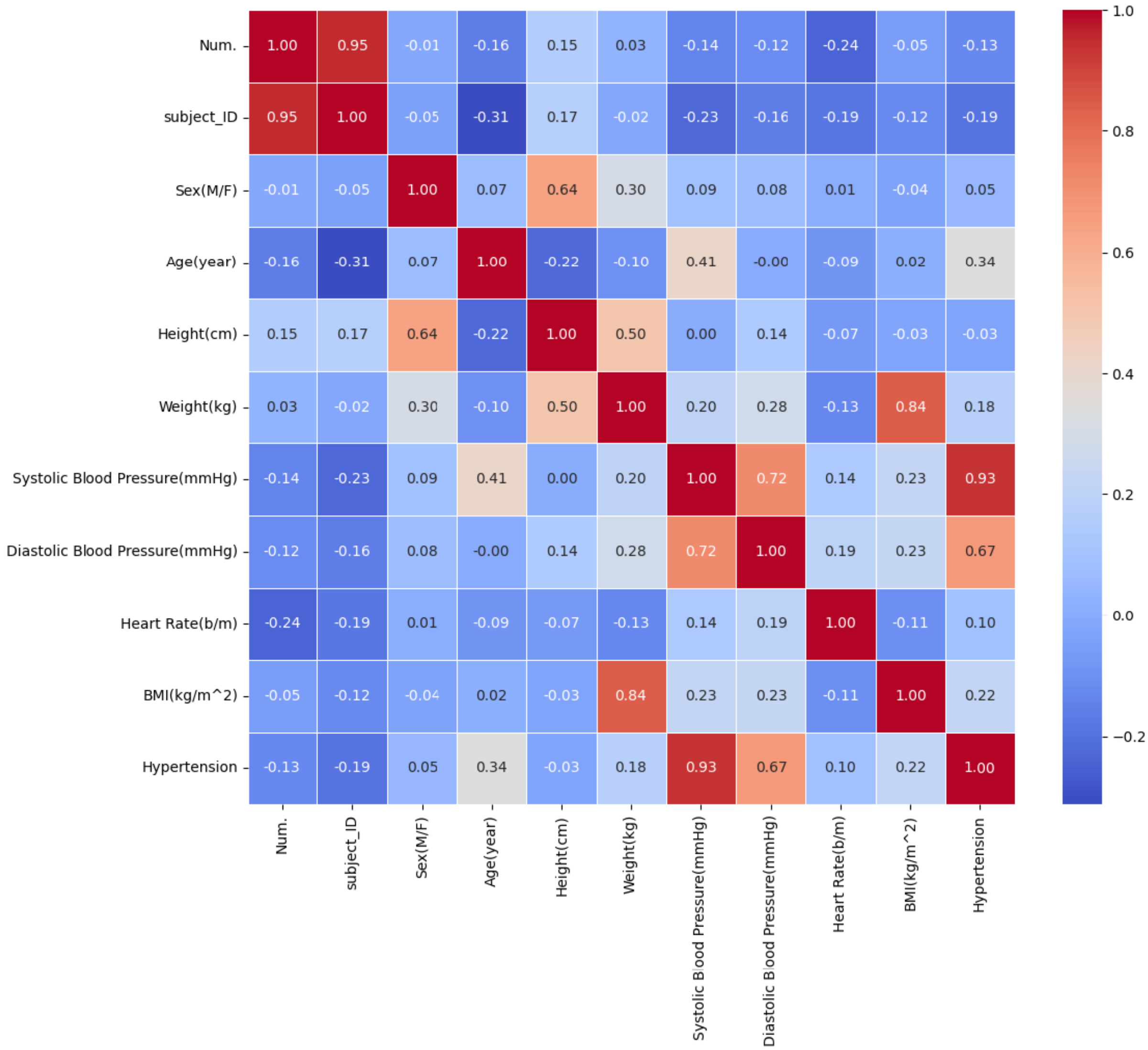


FIGURE 2. **Matrix showing the correlation among variables in the employed dataset.**

1) RF-BASED FP AND LSTM

Random Forest (RF) is an effective ensemble learning approach that combines many decision trees to enhance predictive accuracy and robustness. More specifically, RF works by creating numerous decision trees using different subsets of the dataset and taking the average or majority vote of their predictions. Random forest has very little chance of overfitting on high-dimensional data. Additionally, the feature importance scores provided by RF are useful for understanding complex relationships within the data and choosing important features for prediction tasks.

$$\hat{y} = \mathrm{RF}(x) = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \tag{2}$$

Equation 2 shows how the random forest model combines the multiple predictions of multiple decision trees.

2) GB-BASED FP AND LSTM

Gradient Boosting, known as GB, is a method in machine learning that constructs a group of learners, usually decision trees, one after the other. The goal is to reduce a loss function by introducing models that address mistakes made by the current models. GB continuously adjusts models to the differences (or gradients) in the model's forecasts, giving rise to its name "gradient" boosting. This approach proves successful for regression and classification assignments, which frequently produce predictions.

$$\hat{y} = \mathrm{GB}(x) = \sum_{k=1}^{K} f_k(x) \tag{3}$$

Gradient boosting combines the output of multiple weak learners for the final prediction, as shown in Equation 3.

Algorithm 1 Hypertension Detection Algorithm

Input: $X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}}$
Convert labels to categorical
Train a classifier:
$any\_classifier \leftarrow$ Classifier()
$any\_classifier$.fit(X_{train}.reshape(X_{train}.shape[0], -1), y_{train})
Use the classifier predictions as additional features:
any_train_predictions $\leftarrow$ any_classifier.predict(X_{train}.reshape(X_{train})
$any\_test\_predictions \leftarrow any\_classifier$.predict($X_{\text{test}}$.reshape($X_{\text{test}}$)
Combine the original features with classifier predictions

Pad sequences for input data
Reshape data for LSTM input:
$X_{\text{train\_padded}} \leftarrow X_{\text{train\_padded}}$.reshape(($X_{\text{train\_padded}}$ $X_{\text{train\_padded}}$)
$X_{\text{test\_padded}} \leftarrow X_{\text{test\_padded}}$.reshape(($X_{\text{test\_padded}}$ $X_{\text{test\_padded}}$)
Define a simple neural network with LSTM and Dense layers:
model $\leftarrow$ Sequential()
model.add(LSTM(8,activation="relu", input_shape=($X_{\text{train\_padded}}, X_{\text{train\_padded}}$)
model.add(Dense(64, activation="relu"))
model.add(Dense(64, activation="relu"))
model.add(Dropout(0.2))
model.add(Dense(32, activation="relu"))
model.add(Dense(4, activation="softmax"))
Compile the model:
model.compile(optimizer= "adam", loss="categorical_crossentropy", metrics=["accuracy"])
Save the best model during training based on validation accuracy
Train the neural network using the combined features with early stopping and model checkpoint
Load the best model:
tf.keras.models.load_model("best_model.h5")
Evaluate the model on the test set:
$y\_pred \leftarrow model$.predict($X_{\text{test\_padded}}$)
$y\_pred\_classes \leftarrow$ np.argmax(y_pred, axis $= 1$)
$y\_test\_true \leftarrow$ np.argmax($y_{\text{test\_categorical}}$, axis $= 1$)
Calculate accuracy, precision, recall, and F1-score
Print the metrics

3) LR-BASED FP AND LSTM

Linear Regression (LR) is a learning method employed to model the connection between a dependent variable, y and one or more independent variables, x. It presupposes a linear link between these variables and strives to discover a suitable linear model by reducing the sum of squared differences. LR is extensively utilized for forecasting results and drawing conclusions because of its straightforwardness and explainability.

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p \tag{4}$$

Linear Regression calculates the coefficients (β) that reduce the sum of variances between the y values and those predicted by the linear model. This leads to a formula for forecasting y using x values, as shown in Equation 4.

4) XGB-BASED FP AND LSTM

XGBoost (Extreme Gradient Boosting) is a state-of-the-art algorithm of gradient boosting technique accelerated for improved speed and performance. The procedure produces an ensemble of weak learners (mostly decision trees) at each step with optimized objectives instead of minimizing the loss function gradient. Through its two-stage boosting strategy, its ability to regularize training via L1/L2, and its ability to aid in parallel processing, the XGBoost method is highly efficient and effective in both regression and classification tasks. Enter Sklearn. It is scalable, and at the same time, it has gained wide adoption in machine learning competitions.

$$\hat{y} = \text{XGB}(x) = \sum_{k=1}^{K} f_k(x) \tag{5}$$

It utilizes the output of numerous weak learners to predict a final output for the input X shown in Equation 5 by adding each weak learner successively to minimize the overall loss function gradient.

5) DT-BASED FP AND LSTM

A decision tree (DT) is one of the most valued supervised learning algorithms, and it is mostly used for both classifier and regression tasks. It does so recursively into space areas defined by feature values with the goal of making impurity (classification) and variance (regression) decrease at every node. Along every branch, the last element is a prediction or result. Decision trees are close and in clear, logical form and can address both kinds of data, such as numeric and categorical data. Consequently, they need to be fitted on more variability with complex datasets.

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{6}$$

The decision tree output f(x) shown in Equation 6 is mostly used for classification when signs are placed in the equation to show the classes end up being positive (1) or negative (0).

B. EMPLOYED TECHNIQUES

1) LOSS FUNCTION

Cross-entropy loss functions have been chosen due to their good performance in the discriminator's job of separating the two sets. Cross-entropy measures the difference between the actual probability distribution of the labels and the model-deduced probability distribution, which is very relevant for the binary classification problem of new hypertensive detection in this study. It aids in fine-tuning the model by applying a large amount of penalty on the wrong classification, helping in the overall enhancement of the accuracy and convergence rate; the loss function is represented in Equation 7.

$$\text{Categorical Cross-Entropy Loss} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij}\log(p_{ij}) \tag{7}$$

2) OPTIMIZATION

The use of gradient descent as the chosen optimization algorithm is because it is basic to almost every training of neural networks through minimizing the loss function. We chose the Adam optimizer, which is a modification of gradient descent that is better than AdaGrad and RMSProp. The Adam optimizer adapts the learning rate derived per each identity; thus, it is appropriate for the current dataset, which can have noisy and sparse gradients. To make it easier to understand, the research carried out to identify non-stationary objectives and increase the model's convergence speed was the deciding factor. Equation 8 represents the optimization parameter adam.

$$\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\hat{v}_t} + \epsilon}\hat{m}_t \tag{8}$$

3) ACTIVATION FUNCTION

For the layers or neurons in the hidden layers of the LSTM network, the Rectified Linear Unit (ReLU) was used, represented in Equation 9. CNN is used because it does not suffer from the vanishing gradient problem like most deep networks, and ReLU is used because of its simplicity and usefulness in handling the gradient disappearance problem. The addition of non-linearity by ReLU allows the model to learn some of these more advanced patterns in order to enhance the model's capacity to capture the nature of the data pertaining to hypertension.

$$\text{ReLU}(x) = \max(0, x) \tag{9}$$

4) REGULARIZATION

To reduce the issues of overfitting, the dropout regularization was incorporated into the model. It is based on the idea of dropout, which means that during the training session, a number of neurons are temporarily switched off randomly so that the deep neural network learns more about features that will be suitable for generalization for the new data sets. This technique was selected because it is one of the most successful and flexible approaches to increase the generalization of deep learning models in cases where the dataset is small or moderately sized, such as our case here; the cases are shown in Equation 10.

$$\text{Dropout}(x) = \begin{cases} 0 & \text{with probability } p \\ \dfrac{x}{1-p} & \text{otherwise} \end{cases} \tag{10}$$

C. SOFTWARE TOOLS AND LIBRARIES

All the experiments that were conducted in this research were done using several different OSS tools and libraries. Python was used as the main programming language in this work to develop the models and analyze the data. For computations of all the arrays and numerical calculations, the prominent numerical computation library NumPy is used in this project [28]. Python-based machine learning library, 'scikit-learn', was used in the current study for the creation of Random Forest and another classifier, along with accuracy, precision, recall, and F1-score metrics [29]. Both TensorFlow [30] and Keras [31], the two complex deep learning frameworks created by Google, were used in developing as well as in the training of the LSTM network. Data visualization libraries, namely, Matplotlib [32] and Seaborn [33], were used to create different types of graphs, confusion matrices, and ROC curves. These programs have been selected mainly for their stability, simplicity and actively supported community.

IV. EXPERIMENTATION ANALYSIS, RESULTS AND DISCUSSIONS

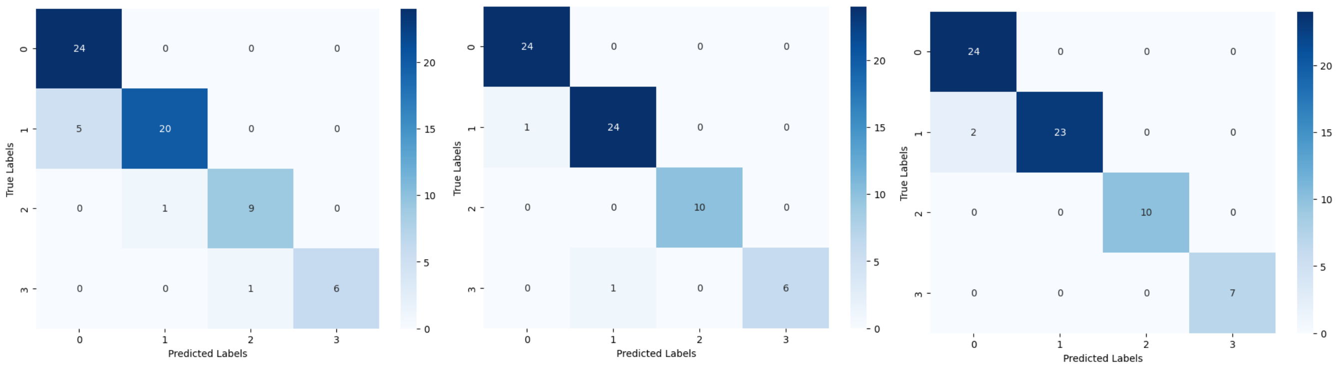
This section expands into the results and experimentation, comprehensively analyzing the machine learning model's performance in hypertension detection. By using colab notebook, experimental outcomes are achieved that are detailed in Table 3 and the time consumed is shown in Table 4, showing the efficacy of various model combinations, shedding light on their accuracy, precision, recall, and F1-score. 70% dataset was used for training and 30% for testing. These results are a critical foundation for solving the intricate interplay between base classifiers and the LSTM neural network. They offer valuable insights into their collective potential for advancing hypertension prediction in healthcare scenarios. Likewise, Table3 presents the experimental results of the trained models, showcasing the performance metrics for various combinations of base classifiers with the LSTM neural network.

TABLE 3. Present the outcomes of the LSTM model across various machine learning-oriented feature prediction (FP) methods.

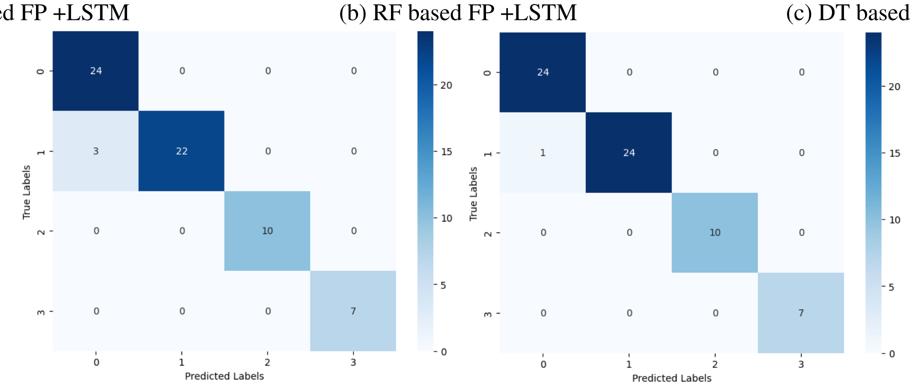
Model Combination	Accuracy	Precision	Recall	F1-score
RF based FP + LSTM	96.97	97.03	96.97	96.93
GB based FP + LSTM	98.48	98.55	98.48	98.48
LR based FP + LSTM	89.39	90.41	89.39	89.30
XGB based FP + LSTM	95.45	95.96	95.45	95.44
DT based FP + LSTM	96.97	97.20	96.97	96.97

TABLE 4. Time consumed by the models to train.

Model Combination	Time(seconds)
RF based FP + LSTM	10.29
GB based FP + LSTM	11.36
LR based FP + LSTM	14.16
XGB based FP + LSTM	9.76
DT based FP + LSTM	13.68



(a) LR based FP +LSTM (b) RF based FP +LSTM (c) DT based FP +LSTM



(d) XGB based FP +LSTM (e) GB based FP +LSTM

FIGURE 3. Confusion Matrix for Evaluating Model Performance in Hypertension Prediction.

Table 5 provides the architecture of a deep lstm model, consisting of each layer's type, output shape, and the number of parameters. The model begins with an LSTM layer, which generates an output shape of (1, 8) and contains 416 parameters. Following the LSTM layer, the first dense layer has an output shape of (64,) with 576 parameters, while the subsequent dense layers have output shapes of (64,) and (32,) with 4160 and 2080 parameters, respectively. A dropout layer is then applied with no output shape specified, as its purpose is to prevent overfitting by randomly dropping some neurons' outputs during training. Finally, the model ends with a dense layer serving as the output layer, producing an output shape of (4,) representing the number of classes in the classification task, with 132 parameters. Overall, this architecture illustrates a combination of LSTM and dense layers with varying output shapes and parameter counts tailored to the specific task. Subsequently, Table 6 outlines the used classifiers parameters while employing the predictive modeling.

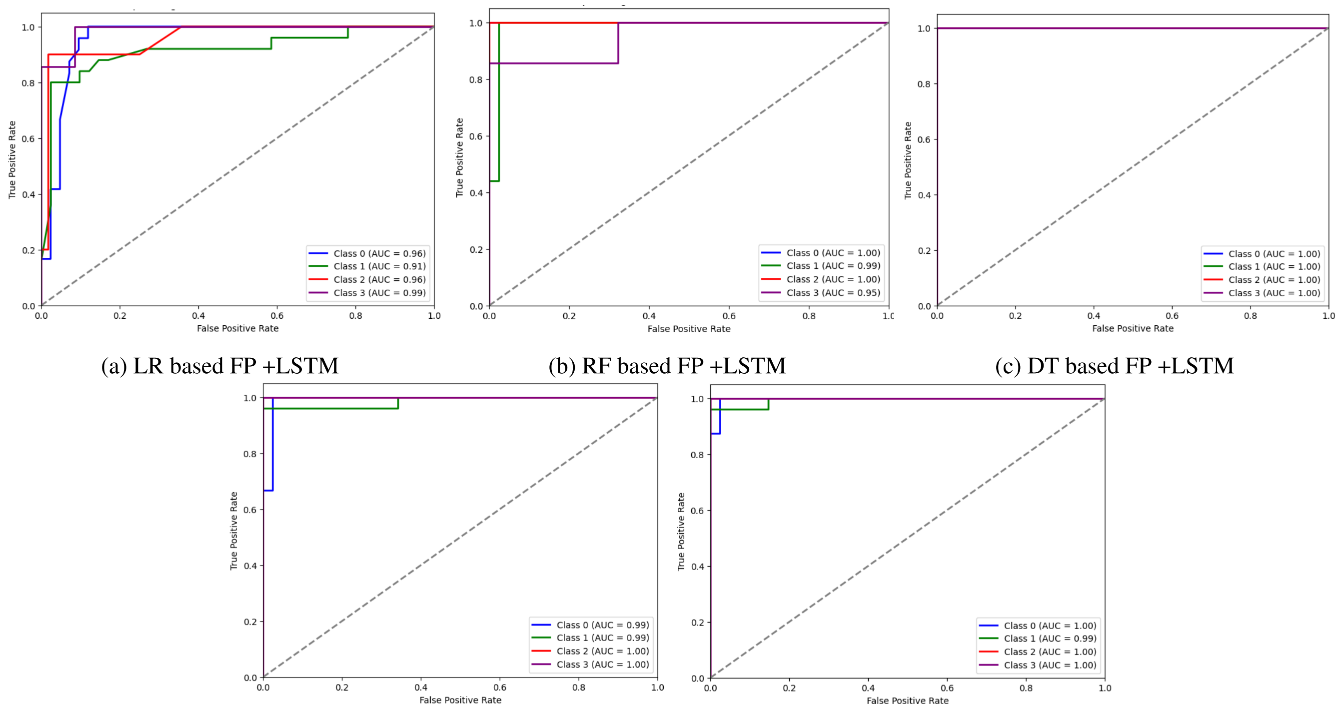
The RF-based FP and LSTM initially achieved good results, with an accuracy of 96.97%, demonstrating the effectiveness of integrating tabular information with ensemble learning. Subsequently, the GB-based FP and LSTM combination outperformed the other models, reaching an accuracy of 98.48%. Likewise, this improvement suggests the potency of boosting algorithms in conjunction with LSTM for hypertension prediction. On the other hand, the LR-based FP and LSTM yielded a lower accuracy of 89.39%, indicating a potential limitation in the linear relationship modeling of

TABLE 5. LSTM neural network architecture.

Layer Type	Output Shape	Parameters
LSTM	(1, 8)	416
Dense	(64,)	576
Dense	(64,)	4160
Dropout	(64,)	-
Dense	(32,)	2080
Dense (Output)	(4,)	132

TABLE 6. Classifier parameters.

Classifier	Parameters
LSTM	- Units: 64 - Return Sequences: True - Activation: Relu - Loss: Categorical Cross Entropy - Optimizer: Adam
GB	- Loss: log - Learning Rate: 0.1 - Criterion: Friedman Mse - N Estimators: 100
DT	- Criterion: Gini - Max Depth: None - Min Samples Split: 2
LR	- LogisticRegression (all default)
XGBoost	- Max Depth: 3 - Learning Rate: 0.1
RF	- Number of Trees: 100 - Max Depth: None



(a) LR based FP +LSTM (b) RF based FP +LSTM (c) DT based FP +LSTM

(d) XGB based FP +LSTM (e) GB based FP +LSTM

FIGURE 4. ROC for Evaluating Model Performance in Hypertension Prediction.

LR when applied to hypertension data. Subsequently, the model's precision and recall values also reflect its challenges in correctly identifying instances of Hypertension. Similarly, the XGB-based FP and LSTM combination showcased a strong performance, achieving an accuracy of 95.45%. This outcome underlines the adaptability of XGB to data, effectively capturing patterns and contributing to hypertension prediction. Next, the DT-based FP and LSTM combination achieved results comparable to those of the RF-based FP and LSTM combination, indicating the effectiveness of DT-based models in tabular data scenarios. Likewise, the findings suggest ensemble methods, particularly GB and RF-based FP, are powerful partners with LSTM in hypertension detection. These models demonstrate high accuracy and robustness in capturing complex relationships within tabular health data. However, while commonly used for binary classification, LR-based FP faces challenges when applied to health data. The limitations in accuracy, precision, and recall highlight the importance of selecting models tailored to the specific characteristics of the dataset. XGB is a strong candidate for hypertension health data, exhibiting competitive accuracy and outperforming some traditional machine learning models. This implies that advanced boosting techniques can significantly contribute to improving hypertension prediction. The consistent performance of DT-based models across different combinations highlights their reliability in handling hypertension health data. This reinforces the notion that DT structures can effectively capture patterns and dependencies in the context of hypertension prediction.

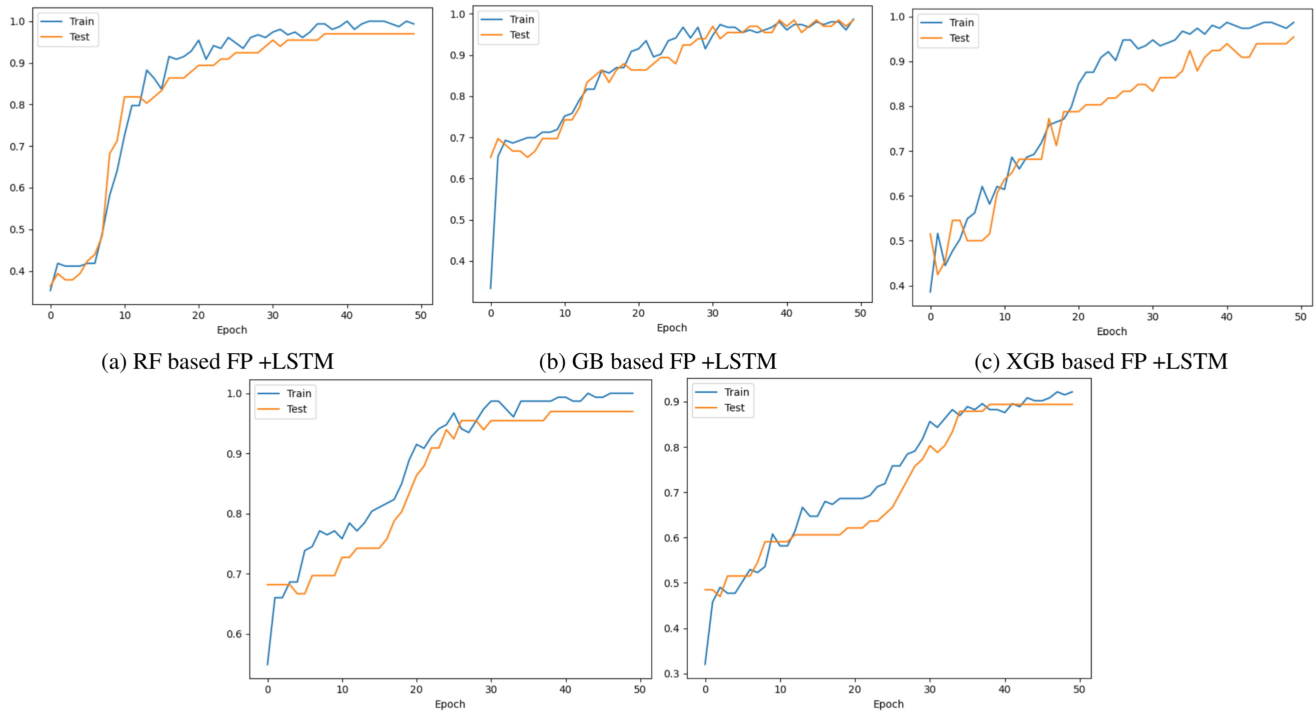
Figure 3 depicts the confusion metrics. The precision and recall analysis based on the results presented in Table 3 provides valuable insights into the performance of the machine learning models for hypertension detection. Precision, representing the ratio of true positive predictions to the total predicted positives, measures the models' ability to avoid false positives. The precision, recall and F1-score calculations are shown in Equation 11, 12 and 13, respectively.

$$\text{Precision} = \frac{TP}{(TP + FP))} \tag{11}$$

$$\text{Recall} = \frac{TP}{(TP + FN))} \tag{12}$$

$$\text{F1 Score} = 2 \times \frac{Precision \times Recall}{(Precision + Recall)} \tag{13}$$

Figure 4 shows the ROC curves. Subsequently, ROC curves are used to evaluate the performance of classification models. These curves show the trade-off between True Positive and False Positive rates at various model thresholds, showing how well a model can differentiate between positive and negative classes. A larger area under the curve indicates better discriminatory power. Next, the GB and LSTM combination exhibit high precision (98.55%), indicating a low rate of misclassifying non-hypertensive instances. However, the LR and LSTM combination show lower precision (90.41%), signaling a comparatively higher rate of false positives. On the other hand, recall, denoting the ratio of true positives to the total actual positives, gauges the models' capacity to



(a) RF based FP +LSTM (b) GB based FP +LSTM (c) XGB based FP +LSTM

(d) DT based FP +LSTM (e) LR based FP +LSTM

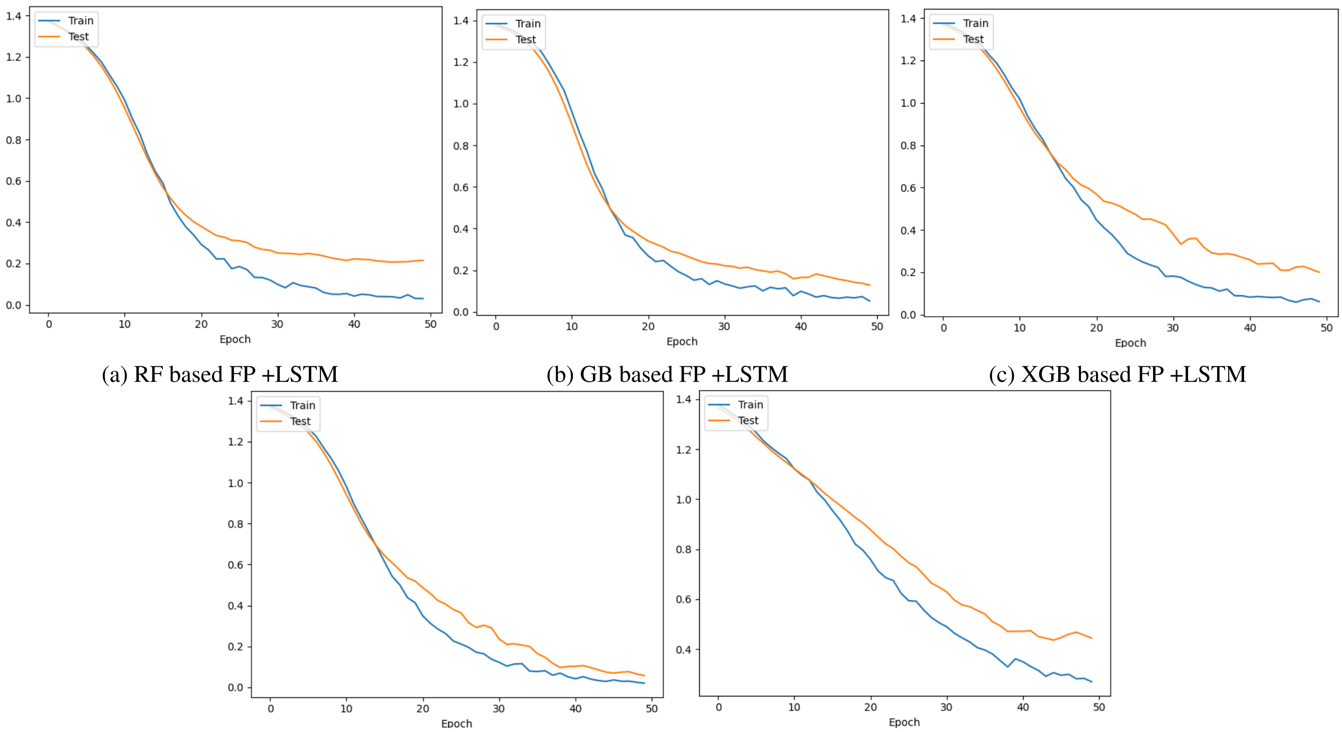
FIGURE 5. Model Accuracy Curves of Training and Testing epochs.

capture all instances of Hypertension. In addition, the GB and LSTM combination excels in recall (98.48%), emphasizing its effectiveness in identifying most cases of Hypertension. On the other hand, the LR and LSTM combination lags in recall (89.39%), highlighting its challenge in capturing the entirety of hypertensive instances. These precision and recall values collectively offer nuanced insights into the models' strengths and weaknesses in hypertension prediction. In summary, the model combinations presented in this study provide valuable insights into the strengths and limitations of different machine-learning approaches for hypertension detection. Overall, the implications of these findings extend to the selection of suitable models for the health data employed in this study and the potential for ensemble methods to enhance predictive accuracy.

The trained models were also evaluated during their training with validation data to observe the trend they followed. They were evaluated using Model Accuracy and Model Loss curves; their results are shown in Figure 5 and Figure 6. The training curves showed quick improvement times, offering insightful information about the learning dynamics of the model. We were able to evaluate the training process' efficacy and spot any abnormalities or inconsistencies in the model's performance track by examining the accuracy curve. LR-based FP +LSTM shown in Figure 5e showed low results, but there were not any irregularities spotted in the proposed model. The loss curves, on the other hand, show how well the model was able to minimize its errors during the training process. A falling loss curve showed that the model was approaching an ideal solution. However, variations or peaks can point to concerns like overfitting or instability during the training phase. None of our models showed any irregularity in the falling curve except LR-based FP +LSTM in 6e and XGB-based FP +LSTM in Figure 6c showed a little deviation. The evaluation helped in accessing the model's generalization to new data and the overall training progress by analyzing the loss curve.

A. DISCUSSION

The proposed model performed well on this dataset, with every model providing high accuracy rates; the trained models include Random Forest (RF), Gradient Boosting (GB), Logistic Regression (LR), XGBoost (XGB) and Decision Tree (DT) integrated with LSTM model. GB gave top-notch performance by providing an accuracy of 98.48%, and RF and DT provided an accuracy of 96.97%. Meanwhile, XGB and LR provided accuracy results of 95.45% and 89.39%, respectively. The new feature production technique provided extra features to the LSTM model that helped the LSTM model to interpret complex data patterns efficiently. It helped the LSTM model to understand the dynamics of the data that lead to enhanced predictive performance. This innovative technique helped to excel in the working of the LSTM model in handling intricate data in different domains. The techniques used previously presented various limitations, including low accuracy, as their models could have been



(a) RF based FP +LSTM (b) GB based FP +LSTM (c) XGB based FP +LSTM

(d) DT based FP +LSTM (e) LR based FP +LSTM

FIGURE 6. Model Loss Curves of Training and Testing epochs.

TABLE 7. Performance comparison with [1].

Reference	Accuracy
[1]	96.20%
GB based FP +LSTM	98.48%

more efficient in learning intricate patterns. Other models like Convolutional Neural Networks (CNN) and SVMs reach a point where they start overfitting on the data, especially when the available dataset is small in quantity or consists of irregular data. These models are also open for adversarial attacks where a slight variation in input can lead the model to predict inaccurate or false results.

GB-based FP +LSTM provided results of 98.48% that not only surpassed the comparison models but also the baseline approach [1] of this paper with a margin of 2.29%. Table 7 compares the baseline approach with the proposed approach.

Some of the other models also surpassed the baseline approach, including RF-HDLM and DT-HDLM; both models provided an accuracy of 96.97

V. CONCLUSION AND FUTURE WORK

This paper provides the theoretical foundation of a unique classification system that is conducive to the early diagnosis of hypertension using feature engineering based on machine learning with deep learning models. In the case of predictive engineering, the models used include Gradient Boosting, Random Forest, Logistic regression, Decision trees, and XG Boost, but by incorporating LSTM with these models, predictive accuracy was achieved. Remarkably, the overall equity of utilizing Gradient Boosting-based feature predictions combined with the LSTM model sat at 98.48% accuracy. The high accuracy and reliability of the proposed model can be of great importance to healthcare practitioners and policymakers. Prompt diagnosis of hypertension can help to prevent serious health problems, including heart attacks and strokes, kidney failure and other consequences. The blood pressure measurement of our model to analyze and predict trends from raw and large data sets is more sophisticated than the standard diagnostic tools that make use of only occasional and less detailed measurements. The implications of this model lie in enabling the early detection of hypertension and changing the management of hypertension in the clinic. The application of machine learning and deep learning in clinics could mean early prevention and intervention for patients with cardiovascular-related diseases and cut healthcare costs and lives lost due to cardiovascular diseases.

This study offers useful findings directly related to the use of feature engineering that employs machine learning in combination with state-of-the-art deep learning models to identify hypertension. The trends associated with Gradient Boosting and LSTM networks are still a subject of further research. Still, they demonstrate the high sensitivity of analyzed dependencies and shall help enhance the predictive model. This approach can be done for other chronic conditions, as illustrated, emphasizing the modularity and applicability of the employed methodology. Further research may also incorporate other variables, such as the patient's genetics and diet, to improve the accuracy of the model. Further, real-time data acquisition from wearable devices and EHRs may be useful in monitoring the patient's status and assembling alerts for both the patient and health-related personnel. Furthermore, possible biases in the data, as well as the model's ability to perform well with different populations, will also be significant considerations. Some of the general considerations that were identified included patients' rights to privacy and protection of their information to ensure compliance with the law and patient trust.

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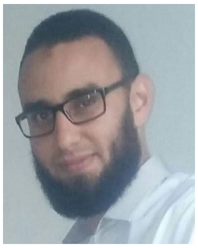
SIDRA ABBAS (Graduate Student Member, IEEE) received the B.S. degree from the Department of Computer Science, COMSATS University Islamabad, Islamabad, Pakistan. She was a Research Assistant with the ASET Laboratories, Islamabad. Her research interests include but are not limited to artificial intelligence, healthcare, mobile ubiquitous computing, computer forensics, machine learning, criminal profiling, software watermarking, intelligent systems, and data privacy protection.

GABRIEL AVELINO SAMPEDRO is currently with e La Salle - College of Saint Benilde, Manila. In past, he has worked with the Faculty of Information and Communication Studies, Philippines Open University, Laguna, Calabarzon, Philippines. His current research interests include the Internet of Things and artificial intelligence.

MOEZ KRICHEN (Member, IEEE) received the Ph.D. degree in computer science from Joseph Fourier University, Grenoble, France, in 2007, and the H.D.R. (Ability to Conduct Research) degree in computer science from the University of Sfax, Sfax, Tunisia, in 2018. He is currently an Associate Professor in computer science with Al-Baha University and a member of the Research Laboratory on Development and Control of Distributed Applications (REDCAD), Sfax. Currently, he is also working on formal aspects related to deep learning, data mining, blockchain, smart contracts, and optimization. His main research interests include model-based conformance, load, security testing methodologies for real-time, distributed, and dynamically adaptable systems. Moreover, he works on applying formal methods to several modern technologies like smart cities, the Internet of Things (IoT), smart vehicles, drones, and healthcare systems.



MEZNAH A. ALAMRO received the Ph.D. degree in computer science from Texas Tech University. She is currently an Assistant Professor in artificial intelligence (AI) with the College of Computer and Information Science, Princess Nourah Bint Abdul Rahman University. Her research interests include machine learning, data mining, and the IoT security.

ALAEDDINE MIHOUB received the Ph.D. degree in computer science from Grenoble-Alpes University, France, in 2015, and the M.Sc. degree in computer science from Paris Descartes University, France, in 2012. He is currently an Associate Professor in artificial intelligence and machine learning with the College of Business and Economics, Qassim University, Saudi Arabia. Previously, he was a Research and Data Scientist with Maskott, France, and, earlier, a Postdoctoral Researcher with the Orange Laboratories, Meylan, France. He is the coauthor of many innovative patents and several publications in well-ranked international journals and conferences. His research interests include smart interactive systems and social signal processing, and, more largely, artificial intelligence, machine learning, and data science.

RASTISLAV KULHANEK received the degree from the Faculty of Electrical Engineering and Informatics, Slovak Technical University, Bratislava, in 2003, and the Ph.D. degree from the Faculty of Management, U.K., in 2019. Subsequently, she worked in several multinational companies in the telecommunications industry in technical and technical-commercial positions in several European countries. She also spent some time freelancing in the IT industry. Since 2006, she has been with the Faculty of Management, Comenius University Bratislava, in the pedagogical and scientific fields. Her primary research interests include management areas in IT, such as service management, management in telecommunications, and project management. She also deals with using mathematical methods and artificial intelligence in management and other industries.