FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 9 No. 3, March, 2025, pp 101 - 106
DOI: https://doi.org/10.33003/fjs-2025-0903-3206

CONCURRENT PREDICTION OF DIABETES AND HYPERTENSION USING DEEP LEARNING

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ABSTRACT

Early detection of diabetes and hypertension is essential in preventing severe complications caused by the diseases. This study developed a prediction model using Feed-Forward Deep Neural Network architecture to predict the diseases. A custom dataset generated by combining features from PIMA Indian dataset and PPG-BP dataset is used in training the model. It achieved 93% accuracy in predicting the diseases. Precision and recall scores were also noteworthy, with 95.5% and 94% for concurrent prediction respectively. These results highlight the model's balanced performance and reliability in real-world healthcare applications. The study addressed limitations in existing single-disease prediction models by focusing on concurrent prediction, which captures the interrelated nature of diabetes and hypertension. Transfer learning played a crucial role in enhancing the model's performance, taking advantage of pre-training of models to overcome challenges like limited labelled datasets and help in making the concurrent prediction possible by sensitizing the model with features relevant for individual disease. This approach reduced computational overhead and improved generalization, making the model practical for deployment in resource-constrained healthcare settings. Feature selection and engineering, driven by Recursive Feature Elimination (RFE) and domain knowledge, ensured the inclusion of the most relevant attributes, further optimizing the model's predictive accuracy.

Keywords: Machine Learning, Deep Learning, Diabetes, Hypertension, Transfer Learning

INTRODUCTION

Two of the most prevalent chronic diseases in the world are diabetes and hypertension. They most times occur together and contribute significantly to mortality and morbidity. Their prevalence is increasing worldwide due to genetic pedigree, changes in lifestyle, and increasing age of the population (Kumar & Clark, 2021). Currently, the focus of most researches is the prediction of either diabetes or hypertension instead of their concurrent prediction. This is disturbing giving their relationship and impact on the health of the populace. Some studies that predict the two conditions often rely on Traditional Machine Learning algorithms and the performance felt short in terms of accuracy. Some researchers applied Deep learning in predicting the two conditions with improved accuracy but still with room for improvement (Gopisetti et al., 2023; Jeong et al., 2022).

Deep learning, a subset of Machine learning that simulate decision-making process of human brain provides an innovative approach to healthcare prediction (Warr, 2020). Deep learning models are very good at analysing complex datasets, such as healthcare dataset by learning hierarchical representations of data. This makes deep learning models ideal for predicting diseases like diabetes and hypertension (Barath, 2021; Kumar et al., 2020).

This study developed a predictive model using deep learning to predict diabetes and hypertension concurrently. The work not only contributes to addressing critical healthcare challenges but also provides a scalable and efficient tool to improve patient outcomes and reduce the burden on healthcare systems globally. Deploying deep learning-based prediction models holds great promise for advancing early detection thereby offering a significant step forward in managing diabetes and hypertension.

Diabetes and hypertension are a major health concern and a high cause of mortality and morbidity, this makes their early detection very important. Recent studies have applied machine learning (ML) and deep learning in their prediction and management (Yashvanth et al., 2023). ML have shown remarkable performance in predicting diseases with random forest as one of the top performing algorithms for diabetes prediction (Stephen et al., 2023). Random forest and Support vector machine (SVM) have shown a better performance in terms of accuracy in hypertension prediction (Stephen et al., 2023). However, data quality and availability still present a great challenge, which can affect the performance of the model (Yashvanth et al., 2023). Mobile health (mHealth) systems equipped with ML algorithms have potential to improve management of diabetes and hypertension, but further research is needed in that regard (Afsaneh et al., 2022; Stephen et al., 2023). Application of DL algorithms in diabetes prediction has shown that they have outperformed conventional machine learning algorithms. For example, Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model achieved 95.1% accuracy in diabetes prediction (Balaji & Sugumar, 2022).

A personalized healthcare monitoring system for diabetes patients was introduced in (Alfian et al., 2018), which incorporates wearable sensors and Machine Learning technology. The system makes use of Bluetooth Low Energy-based sensors for data collection. The researchers employed multi-layer perceptron and LSTM algorithms to classify the diabetes type and forecast the glucose level of the user. A bi-directional LSTM was proposed to predict the future level of blood glucose (Qingnan et al., 2019). In that system, the authors compared the results from simple LSTM with Bi-LSTM using 26 datasets from 20 real patients. (H. Zhou et al., 2020) Proposed a diabetes-risk prediction model based on enhanced DNN method, which can predict and identify whether someone will have this disease in the future. Gradient boosting was used on PIMA dataset to predict diabetes by (Ganie et al., 2023) and achieved a very good accuracy. (Gopisetti et al., 2023) Used several classification algorithms to predict many diseases e.g. diabetes, hypertension, kidney disease. This was done with a very good accuracy.

MATERIALS AND METHODS

A feed-forward deep neural network model with four input features, two hidden layers, and an output layer was developed and trained using PIMA dataset to predict diabetes. The FFDNN model is later adjusted using transfer learning for hypertension prediction. Custom dataset was created by combining data from both PIMA dataset and PPG-BP dataset. Technique such as Recursive Feature Elimination (RFE) was used in conjunction with domain knowledge to select features that are relevant to both diseases. RFE eliminates features that contribute less in the prediction of the outcome while Domain knowledge is used in validating the chosen features making sure that they not only have statistical relevance but also clinical importance. This ensured that only the most relevant features were used, thus improving model performance. The FFDNN architecture is modified to adopt a Multi-task learning model architecture; this is done by maintaining the backbone layers and dividing the task-specific layer into two each representing one condition.

Model Development

The feed-forward deep neural network (FFDNN), initially trained to predict diabetes using the PIMA dataset, was modified using transfer learning techniques to predict hypertension. The original model processes features such as glucose, BMI, diabetes pedigree function, and age, using multiple hidden layers with ReLU activation functions to capture complex relationships. After training on features selected from the PIMA dataset, the model's early layers, which learn general representations of diabetes, were frozen, and later layers were replaced, fine-tuned, and trained on features selected from PPG-BP dataset. This fine-tuning adapts the model to hypertension prediction by focusing on features specific to the PPG-BP dataset, such as systolic blood pressure (SBP) and diastolic blood pressure (DBP). The weights learned during diabetes prediction provide a strong foundation for hypertension prediction by taking advantage of shared patterns in the data.

The model was further modified to adopt a multi-task learning (MTL) framework for concurrent prediction of diabetes and hypertension. This involves shared hidden layers to learn common representations across both tasks, followed by task-specific output layers. The input features selected for this model include glucose, BMI, age, and SBP, as these are highly relevant to both conditions based on feature importance and domain knowledge. The architecture consists of three hidden layers with 64, 128, and 64 neurons, and task-specific layers respectively, to balance model complexity and computational efficiency. Dropout regularization (rate = 0.5) was applied to mitigate overfitting, and the output layers consist of two neurons with sigmoid activation functions to produce independent binary outcomes for diabetes and hypertension. The labels for the outcomes are 0 (absence) and 1 (presence) for both diseases, ensuring clarity in predictions. Parameter tuning was performed to optimize the model for concurrent prediction. The learning rate was set to 0.001 after experimentation, and the Adam optimizer was used for efficient gradient updates. The batch size was chosen as 32 to balance convergence speed and memory usage, while the number of epochs was set to 50, based on early stopping to prevent overfitting. The binary cross-entropy loss function was used for each task, ensuring the model accurately predicts the binary outcomes. These modifications and parameter choices ensure the model is robust and capable of using shared and task-specific patterns, and well-suited for real-world healthcare scenarios where diabetes and hypertension often coexist. The modified model is shown in the figure below:

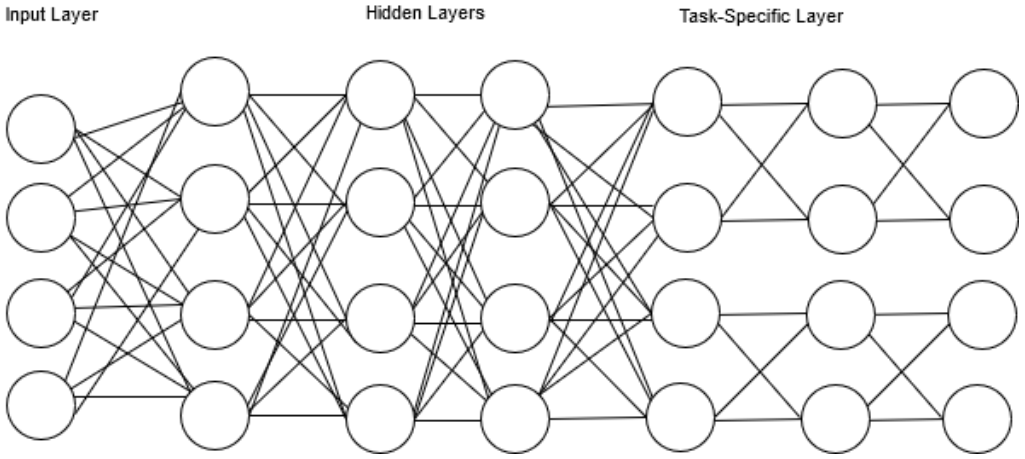

Figure 1: Feed-Forward Deep Neural Network Model

Dataset Collection

A custom dataset was created in this work by combining features from PIMA Indian Diabetes dataset and Photoplethysmography Blood Pressure (PPG-BP) dataset. Features relevant to the prediction of these conditions were provided by the datasets. PIMA dataset provides diabetes-related features like glucose, age, body mass index (BMI), and diabetes pedigree function (DPF) while PPG-BP dataset provides hypertension-related features like systolic and diastolic blood pressure. Using this custom dataset enables training a model on features from both datasets, which will enable concurrent prediction of the conditions.

The first step taken in creating the custom dataset is pre-processing the individual datasets to remove outliers, taking care of the missing or incorrect values, and balancing the datasets. Incorrect and missing values are replaced by imputing the median of the corresponding columns. Synthetic Minority Oversampling Technique (SMOTE) is applied to remove the bias in the PIMA datasets that is biased towards the negative outcome. After pre-processing, features are selected from each dataset that are relevant to the conditions each dataset is representing. Glucose, BMI, and blood pressure are selected from PIMA dataset base on their established relationship with the onset of diabetes (Clark & Clark, 2016). Similarly, systolic blood pressure, diastolic blood pressure, and PPG signals are selected from PPG-BP dataset; these are critical indicators of hypertension (Heart Association, 2021). The features are then standardized to

ensure they are on comparable scales in order to avoid the model being influenced by any dataset's features.

Meaningful alignment of features was done in order to simulate a realistic health profile. Subject health profile was constructed since the datasets comes from different origin and therefore have no shared identifies. This construction involved making sure there is logical consistency between features for example, correlating higher glucose levels and BMI with elevated blood pressure readings base on established medical literature (Rushakoff, Sullivan, et al., 2017; Sheen et al., 2020; Song et al., 2023). Label creation for concurrent prediction involves using binary labels for diabetes (from the PIMA dataset) and hypertension (derived from thresholds in SBP and DBP values in the PPG-BP dataset, such as SBP ≥ 140 mmHg or DBP ≥ 90 mmHg, as per WHO guidelines).

By integrating features from these datasets, the combined dataset facilitates the concurrent prediction of diabetes and hypertension. The combined dataset is highly compatible with transfer learning, as the model can take advantage of patterns learned during diabetes prediction (using PIMA) and adapt them to hypertension prediction (using PPG-BP). Transfer learning ensures that shared representations, such as correlations between BMI, glucose, and blood pressure, are reused effectively, reducing the need for extensive retraining on hypertension-specific features while improving overall model efficiency and performance (Pan & Yang, 2020).

Table 1: Dataset Description

S/No.	Attribute	Data type	Note
1.	BP_PIMA	Numeric	Blood Pressure from PIMA Dataset
2.	Glucose	Numeric	Plasma glucose level two hours after consuming glucose. From PIMA
3.	Systolic Blood Pressure	Numeric	Systolic Blood pressure (mmHg) from PPG-BP
4.	Diastolic Blood Pressure	Numeric	Diastolic Blood Pressure (mmHg) from PPG-BP
5.	PPG	Photoplethysmography	Normalized photoplethysmography signal from PPG-BP.
6.	Body Mass Index	Numeric	An index used to evaluate a person's relative weight (weight (kg)/height (m^2)) from PIMA
7.	Diabetes Pedigree Function	Numeric	A value that measures genetic risk factors based on a family history of diabetes from PIMA.
8.	Age	Numeric	Age in years from PIMA.
9.	Hypertension	Boolean	Result (true or false)
10.	Diabetes	Boolean	Result (true or false)

Dataset Pre-Processing

Even though the individual datasets were pre-processed before the generation of the custom dataset, some pre-processing was still done. The initial pre-processing of the dataset involves handling missing values, standardizing feature scales, and aligning feature formats from the PIMA and PPG-BP datasets. Missing values are addressed using imputation techniques such as mean or median substitution for numerical data, ensuring no information gaps that might hinder the model's learning process. Additionally, features like glucose levels, systolic blood pressure (SBP), and diastolic blood pressure (DBP) are normalized using StandardScaler to ensure all variables are on a similar scale, preventing disproportionate influence during training. Finally, the combined dataset is shuffled to eliminate any biases due to data order and split into training, validation, and test sets. This ensures that the model can generalize well to unseen data, laying a robust foundation for training the concurrent prediction model.

Feature Selection

Feature selection method used in this work combined automated technique with domain knowledge. This is used in order to enhance the feature selection process by taking advantage of the strength of the two (Dash et al., 2022; Farahani et al., 2021). Recursive Feature Elimination (RFE) method of feature selection is the automated technique used in selecting features. RFE method works by generating feature importance and removing the least significant features based on their contribution to the model's predictive performance. Feature importance score is generated using Random Forest for the dataset and from it, least important features are eliminated. It is shown in Table 2 below.

Table 2: Feature Importance Score

Feature	Score
Glucose (PIMA)	0.089858
BMI (PIMA)	0.086946
SBP (PPG-BP)	0.084037
Age (PIMA and PPG-BP)	0.079373
DiabetesPedigreeFunction (PIMA)	0.075987
PPG_Amplitude (PPG-BP)	0.073833
DBP (PPG-BP)	0.072418
BloodPressure (PIMA)	0.068694

Glucose, BMI, Systolic Blood Pressure (SBP), and Age are chosen as the most relevant features based on their feature importance score; this is corroborated by domain knowledge. These features demonstrated a strong correlation with the target variables (diabetes and hypertension), for instance, glucose levels consistently ranked as the most important feature for diabetes prediction, aligning with the pathophysiological mechanism of the disease, where hyperglycemia is a primary indicator (DeGuire et al., 2019; B. Zhou et al., 2021). Similarly, BMI emerged as a critical

feature due to its strong association with insulin resistance and cardiovascular risk factors, making it a significant predictor for both conditions (Rushakoff, Rushakoff, et al., 2017). Also, domain knowledge has shown that systolic blood pressure (SBP) is a key feature for hypertension prediction as it directly defines the condition (hypertension). Elevated SBP is clinically used as a diagnostic criterion for hypertension (Barhun & Sission, 2023; Kumar & Clark, 2021; Kumari et al., 2021) and its inclusion ensures the model captures the cardiovascular risks associated with both diabetes and hypertension (Heart Association, 2021). Additionally, age is another pivotal feature, as the likelihood of developing diabetes and hypertension increases with age due to progressive vascular changes and metabolic dysfunction (Williams & Farrar, 2018). By selecting these features, it is ensured that the model uses features that are both statistically relevant and clinically significant, ensuring it focuses on the most impactful features while reducing noise from less relevant ones.

Evaluation Metrics

This section presents the metrics used in evaluating the performance of the model. The prediction process comprises of four different results known as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The performance of the model is evaluated using metrics like accuracy, precision, and recall.

Accuracy is computed using the ratio between the number of correct predictions (true positive and true negative) over all the predictions made by the model. It is calculated by the equation below.

$$\text{Accuracy} = \frac{TP+TN}{TP+FT+FN+TN} \quad (1)$$

Whereas Precision measures the degree to which the model's positive predictions from all of the positive predictions of the classification results are accurate and it is computed by the following equation:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

In addition, the model's recall is a measure of how well it can separate all true positive cases from all the existing positive instances. This is computed by

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

RESULTS AND DISCUSSION

The result of the prediction is presented in table 3 below:

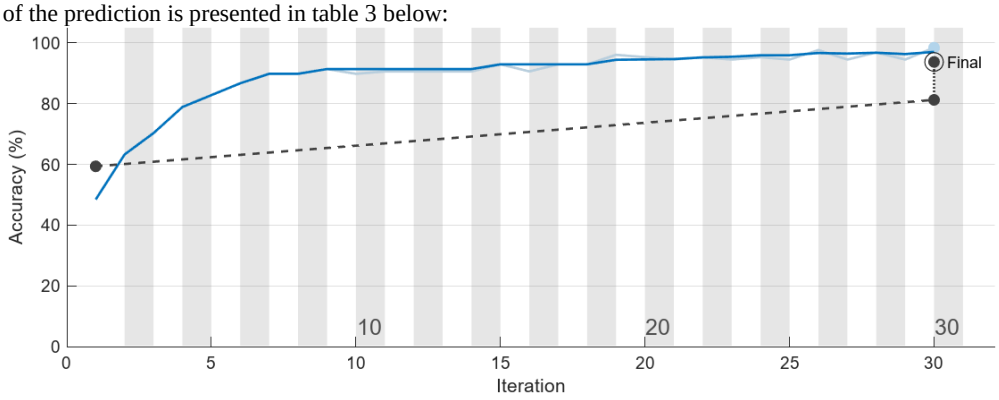

Figure 2: Accuracy for Concurrent Prediction calculated using eq. 1

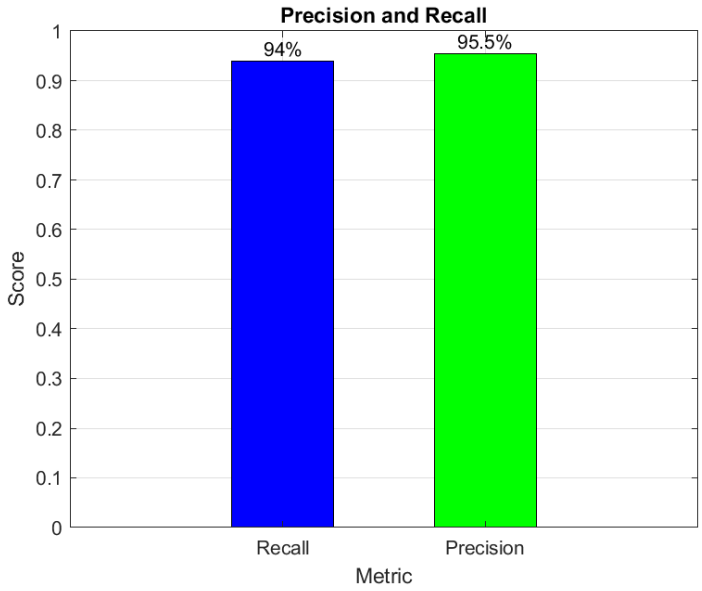

Figure 3: Precision and Recall for Concurrent Prediction calculated using equations 2 and 3

Table 3: Result of the Prediction

Model	Disease	Accuracy	Precision	Recall
Feed-Forward Deep Neural Network with Transfer Learning	Diabetes and Hypertension	93%	95.5%	94%

The Feed-Forward deep neural network model created in this research demonstrated exceptional performance in predicting both diabetes and hypertension concurrently, the model achieved an overall accuracy of 93%. This is a substantial achievement and it demonstrates the model's ability to handle the complexity of multiple disease predictions. The higher precision achieved in this work compared to recall likely reflects a combination of dataset characteristics i.e. imbalance, model design choices, and some evaluation strategies. Research in multi-disease prediction often reports lower accuracies due to the increased complexity as shown in Figure 4 below.

Table 4: Performance of the benchmarked approaches

Model	Disease	Accuracy	Precision	Recall
Support Vector Machine	Diabetes and Hypertension	75%	78%	76.2%
Logistic Regression	Diabetes, Hypertension, and Chronic Kidney Disease	92%	94.1%	93%
Random Forest	Diabetes and Hypertension	92.3%	95.7%	94.5%

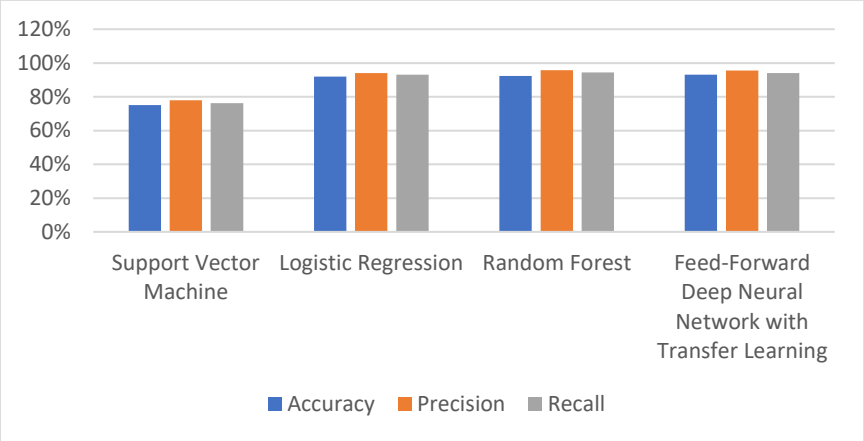

Figure 4: Comparison with benchmarked approaches

The research provides a dual-disease prediction model that enables medical practitioners to efficiently and accurately identify both diabetes and hypertension in patients, facilitating early intervention. This capability can enhance patient management in clinical settings, reduce healthcare costs, and improve overall health outcomes by allowing for timely treatment decisions.

Using transfer learning for medical diagnosis enables models to leverage pre-trained knowledge from related tasks, improving accuracy and reducing training time with limited datasets. This approach is particularly effective for multi-disease prediction as it allows the model to identify shared features and relationships between diseases, enhancing its ability to make concurrent predictions.

The research is limited by its reliance on specific datasets (PIMA Indian and PPG-BP), which may not fully represent diverse patient populations, potentially affecting generalizability. Additionally, the model's performance could be impacted by class imbalance and the inherent noise in medical data, which may lead to biased predictions for certain conditions.

Future work could focus on improving the model by testing it with larger and more diverse datasets to enhance generalizability and robustness. Additionally, incorporating real-time data from IoT devices could facilitate continuous monitoring and more accurate predictions, while expanding the model to include other disease categories would enhance its utility in comprehensive health monitoring systems.

CONCLUSION

This research has succeeded in achieving its objective of creating a model capable of predicting diabetes and hypertension concurrently. The model achieved an accuracy of 93%, 95.5% and 94% precision and recall respectively, which is satisfactory and appropriate result in predicting diabetes and hypertension concurrently. The contribution of this research is that, it has shown that with appropriate feature analysis and selection, transfer learning can be used in complex medical prediction using deep learning. The research has also shown that domain knowledge plays a very crucial role in selecting appropriate feature that can be used in predicting any disease.

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