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HYPERTENSION PREDICTION USING DEEP LEARNING WITH TRANSFER LEARNING TECHNIQUES

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ABSTRACT
Hypertension or high blood pressure is a chronic condition of consistent rise in blood pressure above the identified normal. It significantly increases the risk of cardiovascular diseases when identified at an advanced stage, but when diagnosed and treated early, it reduces the occurrence of life-threatening complications. This research proposes a prediction model using Deep Learning (DL) with Transfer Learning (TL) techniques for early prediction of hypertension. A pre-trained Feed-Forward Deep Neural Network model, initially developed for diabetes prediction using the PIMA diabetes dataset, is fine-tuned for hypertension prediction using the PPG-BP dataset. This approach utilizes the model's ability to transfer learned knowledge, improving accuracy while reducing computational time. The performance of the model is evaluated using accuracy, precision, and recall. It achieved an accuracy of 81.34%.

Keywords: Deep Learning, Transfer Learning, Hypertension, Feed-Forward Deep Neural Network

INTRODUCTION
Hypertension is characterized by consistent high blood pressure, which can cause damages to the heart and blood vessels if not managed effectively. It is a common and serious chronic non-communicable disease. It is globally recognized as a major risk factor for diseases affecting cardiovascular system e.g., coronary heart disease, myocardial infarction, etc. (Unger et al., 2020). These diseases increase the economic burden on individuals by been part of the leading causes of disability, morbidity, and mortality (*Hypertension*, n.d.). World health organization reported that an estimate of 1.28 billion people between the ages of 40 and 79 are affected by hypertension worldwide most of whom are from low and middle-income countries (Kario et al., 2024). Almost half of people affected by hypertension are not aware of their status and only a little above 40% of adults with the disease are diagnosed and treated. Part of the world's plan on non-communicable disease is to reduce the prevalence of hypertension by 33% between 2010 and 2030 (Unger et al., 2020).

The impact of hypertension on public health makes it extremely important to use computational intelligence methods for its prediction. As a subset of machine learning, deep learning is a computer-based modeling technique that uses many processing layers to understand data representation at various levels of abstraction (Mishra et al., 2021). It has proven effective in handling large datasets and producing accurate predictions in healthcare. However, DL models often require large datasets, which are not always available in medical applications (Alzubaidi et al., 2021). Transfer learning (TL) serves as an effective solution for this by utilizing pre-existing models trained on similar tasks, allowing for faster development with smaller datasets. This study integrates DL and TL techniques to develop a hypertension prediction model, fine-tuning a diabetes prediction model for hypertension. Unlike many studies focused solely on clinical data, this research also emphasizes feature selection and performance enhancement, contributing to both the accuracy and efficiency of the predictive model. The contribution of this paper include:

i. Integration of Deep Learning and Transfer Learning.
ii. Improved model performance through feature selection.

Related works
Recent developments in machine learning, deep learning, and artificial intelligence (AI) have produced improved predictive models for various diseases. ML/DL have shown great promise in predicting hypertension by offering improved performance over traditional approaches (Layton, 2024). Several studies have focused on predicting chronic diseases such as diabetes and hypertension by exploring several ML algorithms such as Gradient Boosting, Random Forest, and Neural Networks (Estiko et al., 2024). For instance, Goyal et al., (2020) developed home health blood pressure monitoring system and uses it to evaluate large BP datasets in an uncontrolled home environment. In another research by Chowdhury et al., (2020), Artificial Neural Network (ANN) and Support Vector Machine (SVM) were used to predict hypertension with patient's blood pressure and ECG as the parameters. Predictions that are more accurate were recorded with ANN classifiers. Shrivastava et al., (2023) predicted Systolic and Diastolic blood pressures with a new ML method. They tested four Machine Learning techniques using different rations of data for training, validation, and testing in order to enhance the model's accuracy. Random Forest performed better than all the other algorithms. In their study, Herrera-Huisa et al., (2021) discovered that ML can be used to detect hypertension in COVID-19 patients. They explained that Neural Networks, Random Forest, and XGBoost are the predictive models that allow better detection. Datta et al., (2022) applied Long Short Term Memory (LSTM) network to electronic health record and achieved high accuracy in predicting hypertension. Unlike most studies that focus on either clinical data or physiological signals, Martinez-Ríos et al., (2021) believes that the model's performance can be improved by combining the two.

Transfer Learning
Transfer learning is a technique in machine learning in which knowledge is obtained from a task and used in another task even if it is not strongly related to the original task in order to reduce learning cost, time, and augment in fields where large dataset is not available e.g. medical fields (Farahani et al., 2021; Sablons De Gélis, 2019). Transfer learning has emerged as a useful approach in medical applications where data scarcity is common. Pan & Yang, (2020) demonstrated

how TL could improve predictions in healthcare applications, even with small datasets, by leveraging knowledge from pre-trained models. This research builds on such approaches by using a DNN originally trained for diabetes prediction using the PIMA dataset to predict hypertension using the PPG-BP dataset. By retaining certain layers and fine-tuning others, the model achieves higher accuracy while reducing training time. This approach not only saves computational resources but also ensures that the model is generalizable across related tasks.

MATERIALS AND METHODS

This study adopts a pre-trained FFDNN originally designed for diabetes prediction and fine-tunes it for hypertension prediction. The pre-trained FFDNN achieved an impressive performance with 97.80% accuracy using PIMA dataset. The PPG-BP dataset, containing features like sex, age, systolic and diastolic blood pressure, heart rate, BMI, height, and weight, was preprocessed through cleaning, feature engineering, and normalization. The model was then fine-tuned using Transfer learning techniques. Key improvements were made through feature selection, using a hybrid method combining domain expertise and filter-based selection. Pearson's correlation coefficient was computed to determine relationships between features and outcomes, with features such as systolic blood pressure, diastolic blood pressure, age, and heart rate selected for training. The feature importance scores ensured that only the most relevant features were used, thus improving model performance. The DNN architecture was modified by removing the last hidden layer (task-specific to diabetes) and adding two new hidden layers for hypertension prediction. The remaining layers were frozen to retain the knowledge acquired in diabetes prediction, ensuring the efficient transfer of learned features. The model was then fine-tuned by adjusting hyper-parameters, such as a learning rate of 0.001, mini-batch size of 300, and using the Adam optimizer.

Dataset

The dataset used in this study is Photo-plethysmography-blood Pressure (PPG-BP) dataset sourced from publicly available repositories as indicated in relevant works such as (G. Zhang, 2020; Nour & Polat, 2020; *PPG-BP Database*, 2021)Nour & Polat (2020). The dataset contains the following eight features: sex, age, height (cm), weight (kg), systolic blood pressure (mmHg), diastolic blood pressure (mmHg), heart rate (bpm), and BMI (kg/m2) (Nour & Polat, 2020). In addition, there are four classes as outcomes in the dataset; they include normal (healthy), pre-hypertension, stage-1 hypertension, and stage-2 hypertension. Furthermore, 657 fingertip PPG segments from 219 subjects, ranging in age from 21 to 86, with an average age of 57 ± 16 years, are contained in the dataset. Every segment lasts for 2.1 seconds and uses a 1kHz sampling rate. Each individual has a single measurement of their systolic and diastolic blood pressure (SBP and DBP), together with data related to their age, sex, height, weight, heart rate, and disease status. With a hardware filter bandpass of 0.5–12 Hz, the PPG signal was captured using an SMPLUS SEP9AF-2 sensor that was linked to a Texas Instrument MSP430FG4618 microcontroller. The upper arm blood pressure monitor, Omron HEM-7201, was used to take the blood pressure readings. Although the PPG-BP data is derived from hospital patients, it was collected under controlled circumstances by means of an experimental methodology, and it does not come from intensive care units. After ten minutes of relaxation and adaptation, data collection was done in private with the patients seated in office chairs with their arms resting on a desk. Every subject received the identical acquisition equipment. Additionally, patients with diagnoses other than diabetes and cardiovascular illnesses were removed using a screening process. Additionally, the data was checked for anomalies and missing values. A signal quality index was calculated, and subjects with low values were eliminated, in order to guarantee a constant signal quality (Weber-Boisvert et al., 2023). The attributes of the dataset are listed and described in Table I.

Table I: Dataset Description

S/No	Attribute	Data Type	Note
1.	Age	Numeric	A value that represents the age of a patient.
2.	Height	Numeric	Height of a patient (cm)
3.	Weight	Numeric	Weight of a patient (Kg)
4.	Systolic Blood Pressure	Numeric	Systolic Blood Pressure (mmHg)
5.	Diastolic Blood Pressure	Numeric	Diastolic Blood Pressure (mmHg)
6.	Body Mass Index	Numeric	An index used to evaluate a person's relative weight (weight (kg)/height (m^2))
7.	Heart Rate	Numeric	A value that measures that measures heartbeat of a person per minute.
8.	Sex	String	Gender of the patient
9.	Class	Boolean	Result (true or false)

Dataset Pre-Processing

In this study, various strategies were used for data pre-processing. The first stage is checking all the rows and columns in the dataset. It was discovered that there are 768 rows and 9 columns with neither duplicate nor null value in them as shown in Table 2.

Table 2: Null Values in PPG-BP Dataset

S/No	Column	Non-null count	Data Type
0	Sex	219 non-null	Object
1	Age	219 non-null	Int
2	Height (cm)	219 non-null	Int
3	Weight (kg)	219 non-null	Int
4	Systolic Blood Pressure	219 non-null	Int
5	Diastolic Blood Pressure	219 non-null	Int
6	Heart rate (b/m)	219 non-null	Int
7	BMI (kg/m^2)	219 non-null	Float
8	Outcome	219 non-null	Object

There are no empty or zero values in the dataset (as shown in Tables 3 and 4) and it has four classes as the possible outcomes, this includes normal, pre-hypertension, stage-1 hypertension, and stage-2 hypertension. For easier classification and better readability, the four possible outcomes are converted into two possible outcomes. These are normal as non-hypertensive while pre-hypertension, stage-1 hypertension, and stage-2 hypertension as hypertensive. Even though pre-hypertension and stage-1 hypertension do not necessarily require drug intervention, they are hypertension nonetheless and require doctor's advice for lifestyle adjustment (DeGuire et al., 2019; Unger et al., 2020; Wu et al., 2023). For that reason, they (pre-hypertension and stage-1 hypertension) are merged with stage-2 hypertension and called hypertensive for this work. The outcome is then classified as 1 been hypertensive and 0 been non-hypertensive.

Table 3: Standard Deviation of PPG-BP Dataset

	Age	**Height (cm)**	**Weight (kg)**	**Systolic Blood Pressure (mmHg)**	**Diastolic Blood Pressure (mmHg)**	**Heart Rate (b/m)**	**BMI (Kg/m^2)**
Count	219.00	219.00	219.00	219.00	219.00	219.00	219.00
Mean	57.17	161.23	60.19	127.95	71.85	73.64	23.11
Standard Deviation	15.87	8.20	11.89	20.38	11.11	10.74	4.00
Min	21.00	145.00	36.00	80.00	42.00	52.00	14.69
25%	48.00	155.00	52.50	113.50	64.00	66.00	20.55
50%	58.00	160.00	60.00	126.00	70.00	73.00	22.60
75%	67.50	167.00	66.50	139.00	78.00	80.00	25.00
Max	86.00	196.00	103.00	182.00	107.00	106.00	37.46

Table 4: Null Values in PPG-BP Dataset

S/No	**Column**	**Non-null count**	**Data Type**
0	Sex	219 non-null	Object
1	Age	219 non-null	Int
2	Height (cm)	219 non-null	Int
3	Weight (kg)	219 non-null	Int
4	Systolic Blood Pressure	219 non-null	Int
5	Diastolic Blood Pressure	219 non-null	Int
6	Heart rate (b/m)	219 non-null	Int
7	BMI (kg/m^2)	219 non-null	Float
8	Outcome	219 non-null	Object

Feature Engineering

Feature importance is a technique that calculates a score i.e., degree of importance, for all the input features of a model. A feature with higher score means that it has a bigger contribution to the outcome (*Feature Importance Explained. What Is Feature Importance ? | by Akhil Anand | Analytics Vidhya | Medium*, 202 C.E.). Feature importance score plays an important role in selecting features. These scores help in selecting relevant features for model training.

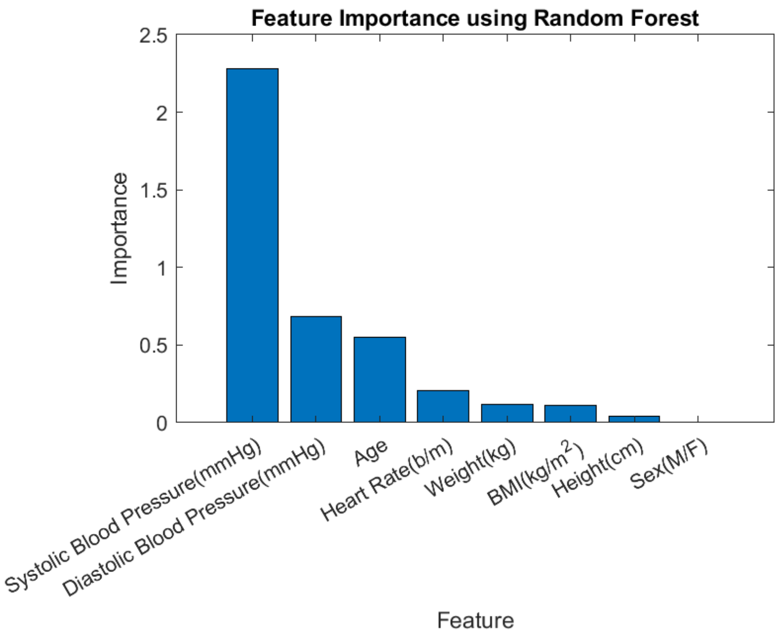

Figure 1: Feature importance Score

Feature Selection

The feature selection method used in this work is Hybrid method. It is a combination of automated technique with domain knowledge; this is used to enhance the feature selection process by leveraging the strength of the two (Dash et al., 2022; Farahani et al., 2021). Filter method of feature selection is the automated technique used in selecting features while domain knowledge is acquired through formal and informal interviews with Internal Medicine specialists. Filter method picks input features based on their positive correlation with the output; correlation analysis was conducted to check that positive correlation between features and outcome. This was done by computing Pearson's correlation coefficient, which measures the strength of the linear relationship between two variables. It is defined as:

$$\rho X, Y = \frac{Cov(X,Y)}{\sigma X \sigma Y} \quad (1)$$

A heat map of the correlation matrix, which is a square matrix that contains Pearson's coefficients computed for all the pairs of variables, is shown below in Figure 2 below.

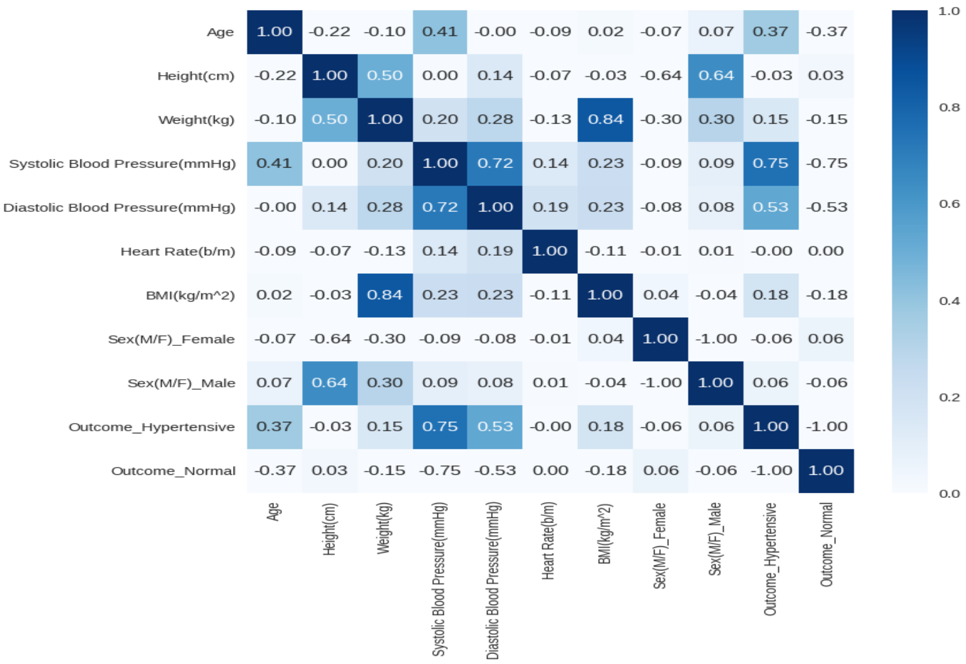

Figure 2: Heatmap of PPG-BP

Systolic Blood Pressure, Diastolic Blood Pressure, Age, and Heart rate scored 0.23, 0.7, 0.6, and 0.3 points respectively in feature importance. These scores make them features that are more important in the dataset. They are also the features more closely related to the outcomes as shown in Figure 4. According to domain knowledge, even though Systolic blood pressure and Diastolic blood pressure alone can be used in diagnosing hypertension, age and Heart rate are also very important determiners for the disease. The four features are therefore chosen. Only four features were chosen, this is to increase the accuracy of the prediction by removing the features that play less role in the overall prediction.

After generating features using feature importance and correlation matrix, domain knowledge was used to validate the relevance of the automatically generated features. Domain knowledge made sure that the features generated made sense within the context of the problem being solved and that they captured the domain-specific issues and exclude those features who even though have statistical significance, lack practical relevance. This enhanced feature selection method used in this work made sure that final features selected are both data-driven and contextually accurate.

Model

The model chosen for this work is Feed-Forward Deep Neural Network with an architecture that includes multiple fully connected layers with ReLU activation, and the final output layer employs the softmax function for classification. Dropout layers were used to prevent overfitting, and the model was trained using stochastic gradient descent (SGD) with a learning rate optimized through cross-validation.

After diabetes prediction using PIMA dataset as the training dataset, Transfer learning techniques are then applied to the model. Some part of the knowledge acquired by the model in predicting diabetes is used in predicting hypertension. This is done by adjusting the model. The first adjustment made is the removal of the last hidden layer of the model; this is because more often than not these layers are task-specific and may not be relevant to the new target task *(Hosna et al., 2021; Zhuang et al., 2020)*. Two new hidden layers replaced the removed hidden layer. This makes hypertension prediction model to have three hidden layers.

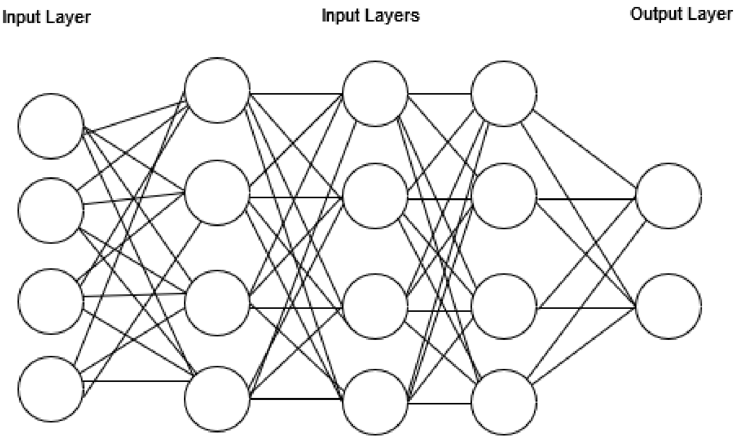

Figure 3: Feed-Forward Deep Neural Network Model Developed

The remaining layers of the model were frozen as the next adjustment; this means that the weights of these layers are not updated during training, only the weights of the newly added layers were learned. Freezing the pre-trained layers helps retain the knowledge learned from the original task and prevents it from been overwritten during training on the target task. This happens especially when the target task has limited data (*Transfer Learning Guide: A Practical Tutorial With Examples for Images and Text in Keras*, 2023; *Understanding Transfer Learning for Deep Learning*, 2021), which is the case in this work. The final adjustment made to the model is fine-tuning of the parameters. The fine-tuning done includes changes in learning rate to 0.001, a lower learning rate is essential to stabilize the weight *(Ciampiconi et al., 2023)*. The mini-batch size is changed to 300. The Adam optimizer and softmax layer used in the original model are all maintained, this is because output classes are two in both cases. The model is then trained using 80% of the dataset and validated with the rest of the data (20%), the data is randomly divided. The prediction is either hypertensive, 1, or non-hypertensive, 0.

Evaluation metrics

This section presents the result and discussion of the prediction. 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.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FT+FN+TN}} \quad (2)$$

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:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (3)$$

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

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (4)$$

RESULTS AND DISCUSSION

Table 5 shows the performance metrics of the model. According to the table, the model achieved 83.21% and 81.34% accuracy on training and testing respectively. Similarly, 89% and 88% precision was achieved and 82% and 80% recall was achieved on training and testing respectively. The result has shown that the proposed methodology has achieved a very good performance in predicting hypertension. The accuracy achieved indicates that the model correctly classified 81 out of 100 instances, meaning that it effectively differentiates between hypertensive and non-hypertensive cases. However, it is noteworthy that accuracy alone may not fully reflect the model's performance, especially when dealing with imbalanced datasets, even though that is not the case with the dataset used in this work. Additional metrics like Precision and Recall are crucial for a comprehensive evaluation of the model’s performance. The model achieved 88% precision indicating that its prediction is correct 88% of the time. This is a strong indicator of the model's ability to avoid false positives. High precision is particularly valuable in medical context, where false positives (e.g., wrong prediction of hypertension in a non-hypertensive patient) could lead to unnecessary interventions or treatments. The high precision achieved by this model suggests a low rate of false alarms, making it reliable for identifying hypertensive patients with high confidence. The recall of 80% achieved by the model indicates that the model correctly identifies 80% of actual hypertensive cases. In other words, it detects 80 out of 100 patients who truly have hypertension. High recall is crucial in medical predictions where failing to identify true positive cases (false negatives) can have serious health consequences. However, achieving a high recall sometimes comes at the cost of precision. In this study, the balance between precision (88%) and recall (80%) indicates a good trade-off, demonstrating that the model does not sacrifice one metric excessively to boost the other.

In predictive modeling, particularly in healthcare, there is often a trade-off between precision and recall. High precision reduces false positives, while high recall reduces false negatives. Depending on the specific application and its critical requirements, one might be prioritized over the other. In this work, achieving a high precision (88%) without significantly compromising recall (80%) suggests that the model maintains a good balance. It is effective in both identifying true hypertensive cases and minimizing incorrect positive predictions. For hypertension prediction, this balance is crucial. While false positives might lead to unnecessary follow-up tests, false negatives (failing to detect hypertension) can have more severe consequences, as untreated hypertension increases the risk of cardiovascular diseases. Therefore, the model's performance with a recall of 80% indicates a reliable ability to detect hypertensive patients.

Table 5: Performance of the Model

Model	Disease	Accuracy		Precision		Recall	
		Training	Testing	Training	Testing	Training	Testing
Feed-Forward Deep Neural Network with Transfer Learning	Hypertension	83.21%	81.34%	89%	88%	82%	80%

Comparatively, a study by (Koshimizu et al., 2020) achieved 81% accuracy using deep neural network with a new loss function. Another study by (Bani-Salameh et al., 2021) achieved 68.7% accuracy using Multi-Layer Perceptron. (Nematollahi et al., 2023) predicts hypertension only in their research and got an accuracy of 81% which is almost the same as the one obtained in this work. The performance of the model in this work is better compared to some of these benchmarks; this is an evidence of the effectiveness of transfer learning in adapting a model trained on one task to another related task.

In this work, hypertension is predicted using Feed-forward deep neural network with Transfer Learning. After successfully predicting diabetes using PIMA Indian diabetes dataset, Transfer learning techniques were implemented on the model before predicting hypertension. Transfer learning facilitated the re-use of knowledge gained from diabetes prediction, thereby enhancing the efficiency and accuracy of hypertension prediction. This approach proved effective as the model achieved an accuracy of 81.34% in predicting hypertension. While this may not be the best result, it still represents a significant predictive capability. The accuracy achieved suggests potential areas for further improvement, possibly through enhanced feature engineering and model optimization.

CONCLUSION

This research has successfully predicted hypertension using Feed-Forward Deep Neural Network with Transfer Learning. Removing irrelevant and duplicate data, deleting outliers, and clearing of formats are some of the cleaning techniques and a number of pre-processing methods were used to improve the dataset's quality. A very good accuracy of 81.3% was achieved. The use of transfer learning techniques has shown that it is possible to augment the model's performance by reducing the need for extensive computational resources and time. It also makes it highly scalable and adaptable to various healthcare settings, which is essential for its practical application.

This study has also shown the importance of integrating deep learning algorithms with transfer learning techniques by achieving dual-focus approach in prediction, which can simultaneously predict more than one disease. This is an improvement over existing systems that mostly focus on one disease at a time.

In future studies, it is highly recommended to incorporate more advanced artificial intelligence techniques that could enhance the model's accuracy and robustness in handling large and complex medical data e.g., ensemble learning and reinforcement learning. This is because reinforcement learning could help the model continuously improve its prediction capacity by interacting with real-time data when implemented in a health monitoring system as suggested earlier. Ensemble learning on the other hand can combine the strength of multiple models to achieve a better performance.

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