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AI-Based Prediction of Systolic Blood Pressure Using Biometric and Clinical Data

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Abstract

Early and accurate prediction of systolic blood pressure (SBP) is essential for preventing cardiovascular complications and improving patient care. In this study, we examined whether a Multi-Layer Perceptron (MLP) model could effectively estimate SBP by combining several biometric and clinical factors. The dataset involved 128 adults visiting a cardiology clinic and included variables such as age, abdominal circumference, glucose, lipid profiles, creatinine, urea, hemoglobin, hematocrit, and diastolic blood pressure (DBP).

Before training, the data were carefully cleaned and normalized to ensure consistency. An MLP model with a single hidden layer was developed and evaluated using two data-split scenarios (70/30 and 80/20 for training and testing). Several activation functions were explored—sigmoid, hyperbolic tangent, and identity—to determine the most efficient setup. Interestingly enough, the model using sigmoid functions in both layers delivered the lowest testing error (MSE = 0.004) in the 80/20 split, suggesting strong predictive performance.

The analysis revealed that DBP, abdominal circumference, and hemoglobin (HGB) played the most critical roles in prediction accuracy. In addition, urea, hematocrit (HCT), and creatinine showed consistent importance across models with testing errors below 0.046.

Taken together, these results indicate that MLP-based models can be valuable, practical, and interpretable tools for SBP prediction. Incorporating such approaches into clinical practice could support personalized cardiovascular risk assessment and more informed decision-making for patient care.

Keywords: Multi-Layer Perceptron, Nonlinear Modeling, Systolic Blood Pressure, Variable Importance Analysis.

JEL Codes: C45, I10, C53, C51

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1. Introduction

Cardiovascular diseases (CVD) remain one of the leading causes of mortality worldwide, highlighting the importance of early diagnosis and effective treatment strategies (WHO,2021). In recent years, artificial intelligence (AI) has brought a remarkable shift to this field, offering powerful tools that assist clinicians in various stages of patient care (Jiang, 2017; Topol, 2019; Esteva,2019). While deep learning techniques have shown outstanding performance—particularly in handling complex data such as medical imaging and ECG signals—traditional machine learning algorithms still play a critical role in assessing individual risk factors and supporting patient classification (Shickel, 2017; Rajkomar, 2019).

Systolic blood pressure (SBP) is widely regarded as a key marker of cardiovascular health and an important predictor of morbidity and mortality worldwide. Findings from large-scale epidemiological studies, including the well-known Framingham Heart Study, have consistently demonstrated that elevated SBP has a stronger association with adverse cardiovascular outcomes than diastolic blood pressure (DBP), particularly in individuals over the age of 50 (Franklin, 2005). Notably, even when DBP levels remain within the normal range, increased SBP has been linked to a higher risk of myocardial infarction, stroke, heart failure, and chronic kidney disease (Chobanian, 2003; Lewington, 2002). Consequently, recent clinical guidelines place greater emphasis on identifying and managing isolated systolic hypertension, especially among older adults.

SBP is also a more sensitive indicator of vascular aging and long-term cardiovascular risk because it is more likely to rise with age as a result of arterial stiffening and decreased vascular compliance (Franklin, 2005). As a result, precise and ongoing SBP estimation has emerged as a key goal in remote patient monitoring and preventive cardiology.

The emergence of artificial intelligence and machine learning has opened up new opportunities in healthcare, particularly in the realms of predictive models, which can significantly improve patient care. One of the main areas of interest in recent years has been the use of neural networks for complex, non-linear data analysis and prediction of disease rates among healthcare professionals. Increasingly, they are used for various purposes, including aiding in the diagnosis of diseases and anticipating patient outcomes, while uncovering subtle patterns and relationships that are often not captured by conventional statistical methods (Jiang, 2017; Hannun, 2019; Shamshirband, 2021).

Predictive models that support early diagnosis and risk assessment have been made possible by the expanding availability of structured clinical and biometric data in the healthcare industry, including blood chemistry, anthropometric measurements, and vital signs (Shamshirband, 2021, Si, 2021). The Multi-Layer Perceptron (MLP) is still one of the most popular and successful machine learning techniques, especially when dealing with structured, tabular datasets (Saraswat, 2024; Dweekat, 2022; Riina,2024). Without requiring very large datasets or a lot of processing power, MLP's adaptable architecture allows it to effectively capture intricate, non-linear relationships between clinical variables.

MLPs are particularly well-suited for biomedical research, where reproducibility and transparency are crucial, because they are comparatively easy to design, train, and interpret in contrast to many specialized deep learning architectures. Furthermore, they have become a more viable and reliable choice in contemporary clinical decision support systems due to their versatility in solving various problem types, such as regression, classification, and feature importance estimation.

In this context, the Multi-Layer Perceptron (MLP), a type of feedforward artificial neural network, offers a flexible framework for modeling complex and non-linear interactions among physiological variables. This study explores the predictive capability of MLP for estimating systolic blood pressure (SBP) using biometric and clinical data. The objective is to develop an interpretable model that can assist in personalized cardiovascular risk assessment and support better clinical decision-making.

2. Material and Method

Ethical Statement: The anonymized dataset used in this research was obtained from a publicly accessible source. Since the data are fully de-identified and freely available, formal ethical approval was not required. The dataset was originally collected as part of the author's Master's thesis (Pamukçu, 2010); however, this study applies different analytical techniques and focuses on addressing additional research objectives.

2.1. Multi-Layer Perceptron

A multi-layer perceptron (MLP) is a type of feedforward artificial neural network. It is one of the most basic neural network types for performing a regression and a classification task. In this study, the MLP was used to predict the systolic blood pressure (SBP) with respect to multiple biometric and clinical parameters. An MLP has different layers of neurons and one input layer, one or more hidden layers and one output layer.

In more detail, any given layer has neurons (or nodes) that are completely vital to and exclusive with neurons at the next levels of the layer. The MLP uses backpropagation to adjust the weight of the model to minimize the prediction error (Akın, 2024).

In this study, the architecture of the MLP has an input layer corresponding to the number of parameters (age, glucose etc.), one or more hidden layers with a user-defined number of neurons, and the output layer which is the model that predicts SBP values.

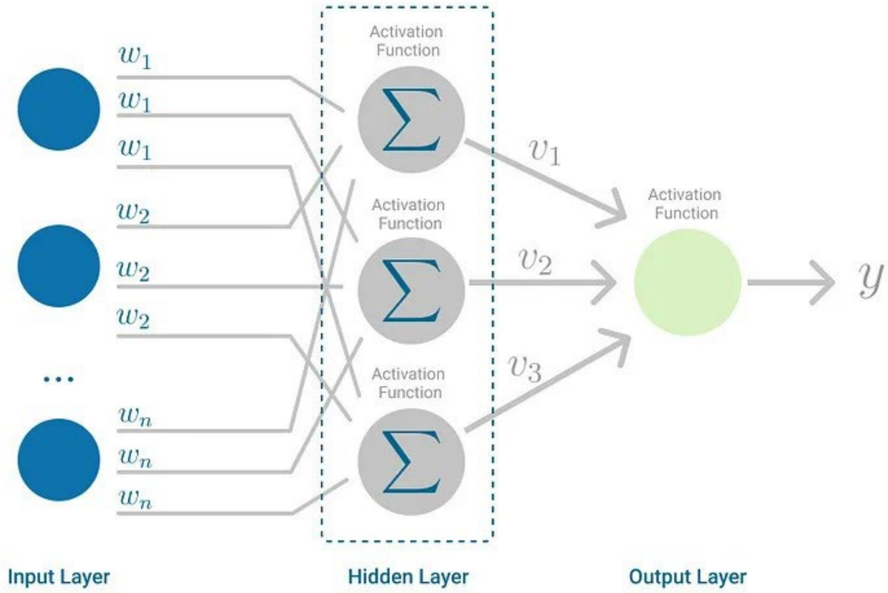

Figure 1. A Multi-Layer Perceptron (MLP) Neural Network Architecture (Rozas-Rodrigez, 2024)

The components of a generic MLP architecture are explained in Figure 1. Each of the blue circles on the left corresponds to the model's inputs. Each of the model inputs is associated with a hidden layer node to which it is connected via the links w_1,w_2,…,w_n. The nodes in the middle, illustrated with sigma Σ symbols, act on the inputs via some activation functions. Each node, within the limits of some activation function, computes the weighted sum of inputs connected to it. The blue node to the right is the model's final output, y. Each hidden layer node is connected to the output node, with the output layer weights being v_1,v_2,…,v_n. The blue circles on the left are the weights associated with the hidden inputs, and the blue circles on the right are the weights associated with the output of the hidden layer inputs. The model refinements are made by optimizing these weights. The diagram illustrates a simple view of a neural network, which entails the movement of data from the inputs to the outputs. Each layer's nodes illustrate the different levels of processing within the model.

2.2. Study Design

The study explored different activation functions in various MLP architectures with one neuron output layer, designed to predict both systolic and diastolic blood pressure. This approach aims to identify the optimal design for accurate estimation by capturing complex relationships between biometric and clinical features. A dataset containing various biometric and clinical variables was used in the study. Data from patients who came to the cardiology clinic of Fırat University Hospital between October 1, 2009 and December 22, 2009 were collected prospectively.

The data are publicly available at:

https://tez.yok.gov.tr/UlusalTezMerkezi/tezSorguSonucYeni.jsp.

The inclusion and exclusion criteria are as follows:

The inclusion criteria for this study required individuals 1) aged 18 years and older with essential biometric and clinical parameters that were completely collected for the dataset. 2) participants with a history of hypertension or other cardiovascular diseases were included, and the study encompassed both male and female individuals.

Otherwise, the exclusion criteria were meticulously delineated in order to uphold the quality of the information as well as the accuracy of the model. 1) Missing data on systolic and/or diastolic blood pressures, or any other of the primary parameters, resulted in exclusion. 2) Candidates in the study with physiologically unreasonable parameters, such as a systolic blood pressure of 250 mmHg, were likewise excluded. 3) Candidates with chronic renal failure or other terminal illnesses were excluded as well, due to the plausibility of independent effects these conditions might have on blood pressure. 4) Pregnant women were also excluded due to the changes in blood pressure that tend to occur during pregnancy. Moreover, 5) dataset integrity was jeopardized by the inclusion of individuals who are in the advanced stages of any illness, such as febrile diseases or infections, as well as those who take medications that have a direct effect on blood pressure control, for instance, beta- blockers and ACE inhibitors.

2.3. Data Set

The dataset consists of 128 participants, each represented by various biometric and clinical variables that are critical for predicting systolic blood pressure (SBP). The variables include age (Age, in years), and height (Height, in meters). Abdominal circumference (Abdominal Circumference, in meters) and biochemical markers such as glucose level (Glucose, in mg/dL), high-density lipoprotein cholesterol (HDL Cholesterol, in mg/dL), and low-density lipoprotein cholesterol (LDL Cholesterol, in mg/dL) are also included. Additional variables comprise urea level (Urea, in mg/dL), creatinine level (Creatinine, in mg/dL), and potassium level (Potassium, in mEq/L). Hemoglobin concentration (Hemoglobin, in g/dL) and hematocrit percentage (Hematocrit, in %) provide further clinical insights. The dataset also records diastolic blood pressure (Diastolic Blood Pressure, in mmHg) and systolic blood pressure (Systolic Blood Pressure, in mmHg), which serves as the primary outcome variables.

2.4. Data Preprocessing

Thorough and detailed data preprocessing was done so as to ready the dataset for modeling, and to also maximize the prediction performance of the Multi-Layer Perceptron (MLP) model for SBP prediction. The steps for preprocessing included data cleaning, normalization, feature selection, and the division of the dataset into training, validation, and testing subsets.

Data cleaning: the dataset in question was heavily scrutinized and suspected anomalous values were marked. The required variables were all complete, and therefore no imputation was necessary. Data consistency was maintained, and outliers were identified and managed.

Feature Normalization: All continuous predictor variables were manually normalized using min–max scaling prior to neural network training. This step was conducted to ensure that variables measured on different scales contributed proportionally during model learning.

Feature Selection: The input features were age, height, abdominal circumference, glucose, HDL, LDL, urea, creatinine, potassium, hemoglobin, and hematocrit. Systolic blood pressure were chosen as target variable.

Data Splitting: Due to the limited sample size, k-fold cross-validation was not applied, as splitting the data into multiple folds would result in small training subsets and unstable estimations. Instead, two train–test configurations were used for model evaluation:

(1) 70% of the data was used for training and 30% for testing, and

(2) 80% was used for training and 20% for testing.

These splits were selected to assess the generalization ability of the MLP model under different training-data proportions.

2.5. Performance Evaluation

The performance of the Multi-Layer Perceptron (MLP) model for predicting blood pressure was evaluated using multiple regression-based metrics to ensure a comprehensive understanding of the model's accuracy and reliability. The Mean Squared Error (MSE) was employed to measure the average squared differences between the actual and predicted SBP values, providing a clear indication of error magnitude.

3. Results

Blood pressure prediction was performed using a Multi-Layer Perceptron (MLP) architecture. The MLP model was designed with a single hidden layer to balance simplicity and effectiveness. Two activation functions, hyperbolic tangent (tanh) and sigmoid, were tested for the hidden layer to evaluate their impact on predictive performance. For the output layer, three different activation functions (identity, tanh, and sigmoid) were employed to assess their suitability for this regression task. The dataset was divided into training and testing sets using two different ratios: 70% training and 30% testing as well as 80% training and 20% testing. These configurations were applied to investigate how varying the training set size affects model accuracy and generalization.

The multilayer perceptron (MLP) model was implemented using the Multilayer Perceptron procedure in IBM SPSS Statistics. The network consisted of an input layer including all predictor variables, one hidden layer with 5 neurons, and a single-neuron output layer.

Training was carried out in batch mode (the gradient was computed on the whole training set at each iteration). The optimization algorithm was scaled conjugate gradient (SCG). The SCG training options were set as follows: Initial Lambda = 0.0000005 (5×10^{-7}), Initial Sigma = 0.00005 (5×10^{-5}), Interval Center = 0, and Interval Offset = ±0.5, meaning that the network weights were initialized from a uniform distribution in the range [-0.5, 0.5]. All other training settings (e.g. maximum number of iterations and stopping criteria) were kept at the IBM SPSS default values. (IBM Corp.,2020). Predictor importance was obtained from the "Independent Variable Importance" output of the SPSS Multilayer Perceptron procedure, which is based on a sensitivity analysis of the trained network and reported as normalized importance values (0–100%). The results for these experiments are presented in Table 1 and Figure 2.

Table 1. Mean Squares Errors (MSE) Values of the Multi-Layer Perceptron (MLP) Models for Systolic Blood Pressure Prediction Under Different Configurations

Activation Functions		Training	Testing	Independent Variable Importance	Training	Testing	Independent Variable Importance
Output Layer	Hidden Layer	70%	30%		80%	20%	
Identity	**Hyperbolic tangent**	0,235	0,351	DBP, Creatinin, LDL	0,184	0,132	DBP, HCT, Urea
	Sigmoid	0,217	0,167	DBP, Creatinin, Abd. Circ.	0,250	0,227	DBP, Creatinine, Urea
Hyperbolic tangent	**Hyperbolic tangent**	0,046	0,036	DBP, Creatinin, Urea	0,034	0,037	DBP, Creatinine, HGB
	Sigmoid	0,030	0,065	DBP, Abd. Circ., HGB	0,035	0,028	DBP, HCT, Creatinine
Sigmoid	**Hyperbolic tangent**	0,010	0,013	DBP, HCT, HGB	0,009	0,008	DBP, HGB, Urea
	Sigmoid	0,008	0,009	DBP, Urea, Abd. Circ.	0,011	0,004	DBP, Abd. Circ., HGB

The best-performing model was determined based on its lowest testing error. The configuration with a Sigmoid activation function for both the hidden and output layers achieved the best performance:

- **70% Training / 30% Testing Split:** Testing error **= 0.009**
- **80% Training / 20% Testing Split:** Testing error **= 0.004**

These results demonstrate that using the sigmoid function for both layers effectively minimizes prediction error, making it the optimal choice for this analysis.

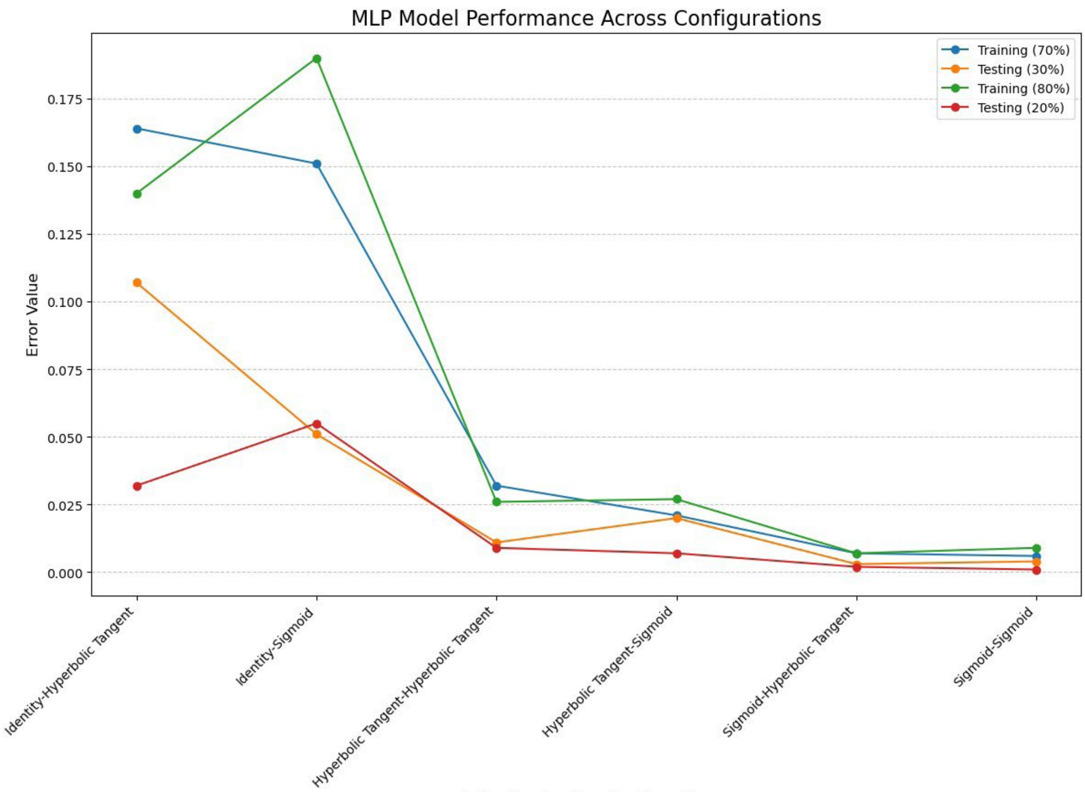

Figure 2. Performance of MLP Models Across Different Activation Function Configurations.
The Bar Chart Illustrates the Training and Testing Error Values for Systolic Blood Pressure Prediction Using Various Combinations of Hidden and Output Layer Activation Functions

The final neural network architecture is illustrated in Figure 3. The model includes 13 predictor variables entered into the input layer, a single hidden layer with five sigmoid-activated neurons, and one sigmoid-activated output neuron predicting systolic blood pressure (SBP).

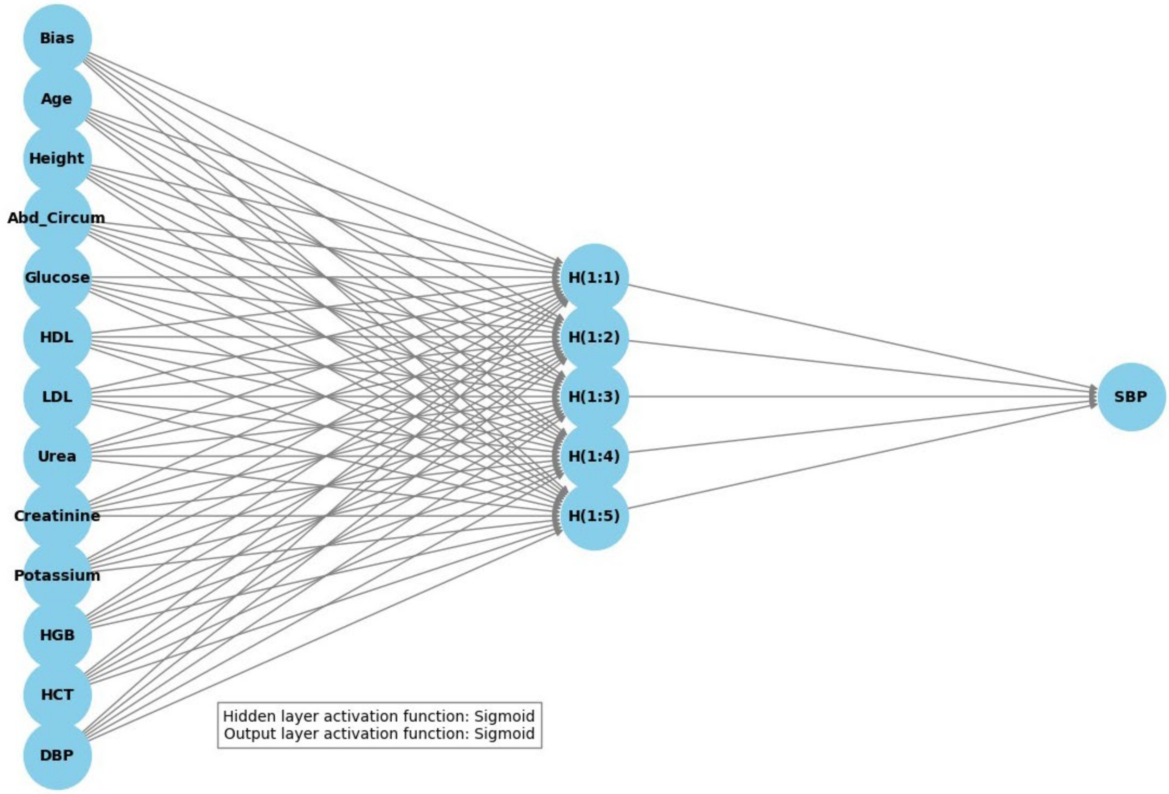

Figure 3. MLP Architecture Used for Systolic Blood Pressure Prediction. The Diagram Illustrates the Configuration of the Multi-Layer Perceptron (MLP) Model With Sigmoid Activation Functions Applied to Both the Hidden and Output Layers

4. Discussion and Conclusion

One of the most adaptable artificial neural network designs, Multi-Layer Perceptrons (MLP) models have found widespread applications across several fields because of their capacity to capture sophisticated, non-linear connections. Their predictive ability and adaptability make them absolutely vital for tackling practical issues.

MLP models are frequently employed in the healthcare sector for diagnosis, disease prediction, and prognosis. For example, MLP models help to forecast cardiovascular disorders by examining risk factors including blood pressure, cholesterol levels, and patient history (Al Bataineh, 2022; Ali, 2023; Subramani, 2023). Medical image analysis also uses these to spot patterns in radiological scans, including tumors in MRI scans or abnormalities in X-rays (Yun, 2019; Yang, 2023). Furthermore in customized medicine, MLPs forecast treatment results based on patient-specific information (Qin, 2022).

Due to the widespread use of MLP models in diverse clinical applications, this study employs an MLP architecture to predict systolic blood pressure — a key biomarker of cardiovascular health. To enable a methodological comparison with conventional statistical approaches, the predictive performance of the MLP model was evaluated using the same dataset previously analyzed by Pamukçu et al (2010). The study reported MSE values of 13,341 for Least Squares Regression-LSR (R^2=0,6003); 13,515 for Ridge Regression-RR (R^2=0,5876), and 13,305 for Principal Component Regression-PCR (R^2=0,5994). In contrast, our MLP model achieved a lower MSE of 0,004 and a higher R^2 of 0,9552 , demonstrating a more accurate prediction of systolic blood pressure in this dataset.

While the RR and PCR models produced more stable predictions in response to multicollinearity and in line with theoretical expectations, they were limited in capturing the complex interactions between explanatory variables. According to variable significance analyses, all three methods (LSR, RR and PCR) consistently highlighted the impact of classic cardiovascular risk factors such as diastolic blood pressure (DBP) and abdominal circumference on SBP. Furthermore, the creatinine was found to be significant in both the RR and PCR models (Pamukcu et al, 2010). The MLP model also highlighted other variables such as hemoglobin (HGB), hematocrit (HCT), and urea as significant contributing factors. This difference reflects MLP's ability to recognize nonlinear relationships.

The component-based structure of the PCR model, in particular, made interpretation difficult, while the

MLP model provided more applicable results with direct variable-based interpretations. This performance improvement highlights the potential advantages of neural network-based approaches over conventional linear models for biomedical prediction tasks, suggesting its better suitability for capturing complex, nonlinear relationships in clinical data.

In conclusion, while classical regression methods provide a solid foundation for SBP estimation, they are limited by linear assumptions. The findings of this study demonstrate that artificial neural network-based models offer more flexible, sensitive, and highly accurate solutions, particularly when working with clinical data containing multicollinearity and complex structures. Therefore, the integration of modern methods capable of modeling nonlinear structures in clinical decision support systems can make significant contributions to applications such as SBP estimation.

Many of the predictors highlighted by our MLP models (including diastolic blood pressure, hemoglobin (HGB), hematocrit (HCT), urea, creatinine, and abdominal circumference) have well-documented physiological and pathophysiological links to blood pressure regulation and cardiovascular risk, which supports the biological plausibility of our findings.

First, although SBP is often emphasized clinically, diastolic blood pressure (DBP) remains an independent and robust predictor of cardiovascular events: large population-based analyses have demonstrated that chronic elevations in both SBP and DBP independently increase the risk of myocardial infarction, stroke, and other adverse outcomes (Flint, 2019). Thus, the strong weighting of DBP in our model aligns with its known clinical relevance.

Second, elevated hemoglobin and hematocrit levels can increase blood viscosity and systemic vascular resistance, potentially contributing to higher systolic pressures. Observational data from adult populations have reported a significant association between higher HGB levels and hypertension (Taha, 2024).

Third, urea and creatinine reflect renal excretory function; impaired kidney function can disrupt sodium-water balance and impair vascular homeostasis, leading to increased blood pressure and hypertension. Epidemiological evidence has consistently shown that compromised renal markers are associated with higher incidence of hypertension and adverse cardiovascular outcomes (De Goeij, 2011; Liu, 2024)

Finally, abdominal circumference is strongly linked to metabolic and hemodynamic derangements including insulin resistance, sympathetic overactivity, endothelial dysfunction, and inflammation; these mechanisms are known to elevate both SBP and DBP (Koenen, 2021)

In summary, the variables identified by our neural-network model are not only statistically significant, but also biologically coherent with known mechanisms of blood pressure elevation and cardiovascular risk.

5. Limitations

The institutional restrictions on data access and variable inclusion were the primary obstacle this study faced. Due to limitations in hospital procedures, the need for extra resources, and the scarcity of equipment, some clinically significant variables could not be gathered. The data collection process was made more difficult by issues with accessing biochemical results, distinguishing between primary and secondary hypertension, and excluding patients taking antihypertensive medication. A secondary limitation is that these restrictions ultimately led to a comparatively small sample size. This small sample size (n=128) inherently reduces the statistical power of the study and limits the generalizability of the findings to broader populations. Additionally, because SPSS applies normalization to the entire dataset before the automatic train–test split, complete prevention of data leakage was technically not possible in this modeling environment.

Therefore, the results should be interpreted with caution, and future research is encouraged to validate the robustness of the model using larger and more heterogeneous samples. To improve the model's applicability in more clinical contexts, future studies should try to validate it using bigger, multi-center datasets with expanded clinical variable sets.

6. Transparency Statement

This study complies with the Transparency and Openness Promotion (TOP) guidelines to ensure research quality, transparency, and openness in research design, data, and materials.

Data Availability Statement: The data that support the findings of this study are openly available in The Higher Education Council National Thesis Center at https://tez.yok.gov.tr/UlusalTezMerkezi/tezSorguSonucYeni.jsp, reference number 23.

Code and Methods: Python and IBM SPSS 27 were used to conduct the analyses. No custom code was created or shared because the study relied on standard statistical procedures that were implemented in these software environments.

Research Materials: The manuscript contains all pertinent methodological information.

Design and Analysis Transparency: The study processes data and performs statistical analysis in accordance with accepted standards. The Methods section provides a thorough description of the research methodology, including preprocessing procedures and statistical methods.

Replication and Reproducibility: With access to the publicly accessible dataset and the standard statistical techniques outlined in the manuscript, the results can be replicated.

Ethical Considerations: The study used openly accessible data, and no human or sensitive data were involved. Therefore, ethical approval was not required.

Conflicts of Interest: The authors declare no conflicts of interest

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