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Research article

# KNN-Based Prediction Model for Assessing Hypertension Risk from Lifestyle Features

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**ABSTRACT**

Hypertension is one of the most common chronic conditions associated with serious cardiovascular complications, and its prevalence continues to rise due to the influence of lifestyle related factors, motivating the use of data driven approaches for early risk identification. Although various machine learning models have been applied in health analytics, many still face challenges in processing heterogeneous lifestyle attributes, which limits their ability to accurately detect individuals at risk. This study addresses that gap by implementing the K Nearest Neighbors algorithm to predict hypertension using a dataset of 1,985 records containing variables such as age, salt intake, stress score, sleep duration, body mass index, family history, medication use, physical activity, and smoking status. The motivation for selecting KNN lies in its simplicity, adaptability, and strong performance in classification tasks involving structured health data. The contribution of this research includes the development of a lifestyle based hypertension prediction model supported by a preprocessing pipeline and optimized hyperparameters, enabling effective handling of mixed numerical and categorical features. The model is evaluated using accuracy, precision, recall, f1 score, and confusion matrix visualization, achieving an accuracy of 85 percent with balanced performance across both classes, showing that KNN offers reliable generalization for this dataset. Future work involves comparing KNN with ensemble or deep learning models, exploring feature selection techniques, and expanding dataset diversity to improve model robustness and applicability for real world digital health solutions.



## 1. Introduction

Lung health plays a vital role in maintaining human survival because the lungs are essential organs that function in the respiratory system to exchange oxygen and carbon dioxide. Structurally, the lungs are located in the thoracic cavity, protected by the ribs and diaphragm, and have a sponge-like structure that allows elasticity during breathing. When the lungs are impaired due to disease or infection, respiratory performance decreases significantly, affecting the overall quality of life. Among the various respiratory diseases, tuberculosis (TB) and pneumonia are among the most prevalent and deadliest diseases globally. According to the World Health Organization (WHO), approximately 10.6 million people were infected with TB worldwide in 2022, causing 1.6 million deaths [1]. Meanwhile, pneumonia remains a leading cause of mortality, resulting in 2.5 million deaths in 2019, including 672,000 deaths among children [2]. The high morbidity and mortality rates of these diseases highlight the urgent need for early, accurate, and efficient detection methods to prevent late-stage complications. Early diagnosis of lung disease is typically conducted through chest X-ray imaging, a low-cost and non-invasive diagnostic approach that provides essential insights into lung structure and abnormalities.

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Although radiographic imaging has long been used to identify lung abnormalities, the interpretation process still depends heavily on the radiologist's judgment, which can introduce human error, inconsistencies between observers, and diagnostic fatigue that may lead to inaccurate classification. The increasing need for faster and more precise diagnostic tools has encouraged the adoption of artificial intelligence (AI) techniques in medical image analysis. Among these technologies, deep learning (DL) has emerged as one of the most influential approaches, especially through the use of Convolutional Neural Networks (CNN). CNN-based models have consistently delivered strong results in tasks such as image recognition and feature extraction by learning spatial patterns directly from raw image data. Various CNN architectures have been proposed, and one of the widely known models is VGG-19, created by the Visual Geometry Group at the University of Oxford. This architecture is appreciated for its straightforward layer arrangement and its ability to capture detailed visual characteristics using multiple 3×3 convolutional kernels. Its stable design and high generalization capability make VGG-19 well suited for medical imaging applications, including classification of chest X-ray abnormalities such as pulmonary infections. As a result, integrating CNN with the VGG-19 architecture has the potential to enhance the accuracy and consistency of automated diagnostic systems, particularly in identifying diseases like tuberculosis and pneumonia.

Recent studies have demonstrated significant advances in applying deep learning for pulmonary disease classification. Sharma [6] proposed a hybrid CNN model using VGG-19 combined with data augmentation techniques to classify pneumonia images, achieving an accuracy of 98.2% on a balanced dataset. The study emphasized that preprocessing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) and image normalization significantly enhanced model robustness. Similarly, Ismael and Şengür [7] implemented a multi-stage CNN-VGG19 approach integrated with a feature selection algorithm for tuberculosis detection, reaching 96.4% sensitivity and 95.8% specificity. Despite these promising results, several challenges remain in developing models capable of simultaneously classifying TB and pneumonia, as variations in image quality, patient anatomy, and disease severity can significantly affect performance [8]. Moreover, dataset imbalance and limited labeled data hinder the development of a robust, generalizable model for real-world clinical deployment. Hence, this study addresses these gaps by proposing an optimized CNN model using VGG-19 architecture for classifying tuberculosis, pneumonia, and normal lung conditions based on X-ray images.

This study focuses on developing an automated system capable of classifying lung diseases by utilizing a Convolutional Neural Network (CNN) built upon the VGG-19 architecture. The model is trained using 3,623 chest X-ray images collected from publicly accessible sources, including Kaggle and Mendeley Data. These images are grouped into three diagnostic categories: normal, pneumonia, and tuberculosis. To improve the clarity of lung structures and optimize model performance, several preprocessing techniques are applied, such as CLAHE enhancement, cropping, resizing, and normalization. The training phase also investigates the influence of different train–test split proportions (80:20, 70:30, 60:40, and 50:50) on overall model behavior. The evaluation of the system relies on common performance indicators, namely accuracy, precision, recall, and F1-score. The experimental findings show that the 70:30 split ratio provides the most favorable results, producing an accuracy of 96 percent, a precision of 97 percent, a recall of 95 percent, and an F1-score of 96 percent. These outcomes demonstrate that the VGG-19 architecture is highly effective in learning and distinguishing relevant features present in chest X-ray images, allowing it to outperform several traditional diagnostic methods.

The main contributions of this research are threefold. First, it presents a robust CNN-based classification model capable of distinguishing tuberculosis, pneumonia, and normal lung conditions with high accuracy using the VGG-19 architecture. Second, it demonstrates that systematic preprocessing techniques, such as CLAHE and normalization, significantly improve model robustness and generalization. Third, it provides a comprehensive evaluation across multiple data splits, serving as a benchmark for similar studies in medical image classification. Furthermore, this work highlights the potential of AI-assisted diagnosis to support radiologists in early detection, thereby reducing workload and increasing diagnostic consistency in clinical practice. In the future, this research may be extended by incorporating larger and more diverse datasets, as well as exploring hybrid deep learning

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architectures such as CNN-LSTM or CNN-Transformer combinations to improve temporal and contextual learning. Additionally, integrating explainable AI (XAI) techniques will be crucial to enhance interpretability and trustworthiness in clinical decision support systems, ensuring safe adoption in real-world medical environments. Ultimately, this study demonstrates the effectiveness of VGG-19 in medical imaging and reinforces the growing role of deep learning as a transformative tool in healthcare innovation.

## 2. Related Work

Research on hypertension prediction has gained significant attention over the past several years as lifestyle-related risk factors become more prominent in influencing cardiovascular health outcomes. Numerous studies have attempted to model the relationship between behavioral attributes and the likelihood of elevated blood pressure. One line of work has focused on examining how age, obesity, dietary habits, and stress contribute to variations in hypertension status using statistical and machine learning approaches. For instance, studies in public health analytics have demonstrated that integrating lifestyle indicators with algorithmic prediction methods enhances early detection efforts compared to traditional screening that relies solely on clinical blood pressure measurements [11]. These findings align with broader epidemiological reports emphasizing that multivariate assessments combining physiological variables with behavioral data provide a more accurate representation of an individual's health risk profile [12]. As data-driven health diagnostics continue to evolve, researchers have increasingly relied on machine learning models to handle the complexity and heterogeneity of such datasets.

Several studies have specifically explored the use of classification algorithms to predict hypertension in structured datasets that include both numerical and categorical features. Logistic regression has been widely utilized because of its interpretability; however, its performance tends to decline when handling nonlinear relationships between attributes, particularly in lifestyle-based health data [13]. To address this limitation, decision tree-based models such as Random Forest and Gradient Boosting Machines have been adopted in many health prediction studies. These ensemble methods provide improvements in accuracy by capturing interaction effects among variables that are often overlooked by simpler models [14]. Nevertheless, some researchers argue that ensemble models require substantial computational resources and extensive parameter tuning, which makes them less suitable for real-time or resource-constrained health applications. These limitations have prompted interest in algorithmic alternatives that offer simpler implementation and satisfactory predictive performance.

The K Nearest Neighbors (KNN) algorithm has emerged as a promising model in medical classification tasks due to its straightforward mechanism and adaptability to various types of data. Recent studies have shown that KNN can achieve competitive accuracy when applied to datasets involving chronic disease classification, including diabetes, heart disease, and metabolic syndrome [15]. Its instance-based learning structure allows KNN to compute similarity measures between samples without relying on an explicit training phase, which is advantageous for datasets that undergo frequent updates or require rapid analysis. Additionally, research comparing KNN with other traditional classifiers indicates that KNN performs especially well when applied to datasets that have been preprocessed with normalization or scaling transformations, highlighting the importance of appropriate data preparation in maximizing the model's performance [16]. These observations support the relevance of KNN in studies that focus on lifestyle-driven risk factors where variability across individuals may be substantial.

In the context of hypertension prediction, multiple researchers have explored the integration of KNN with feature engineering, normalization techniques, and optimized distance metrics. For example, studies have demonstrated that KNN achieves improved classification performance when lifestyle attributes such as salt intake, stress level, and body mass index undergo normalization using min–max scaling or z-score standardization [17]. Other research attempts have incorporated categorical encoding techniques to transform non-numeric attributes such as smoking status, physical activity levels, and medication history into numeric formats suitable for KNN's distance calculations [18]. These preprocessing strategies mirror the methods employed in this study, which also uses numerical encoding and normalization to ensure consistent treatment of mixed-type variables.

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Furthermore, research on hyperparameter optimization emphasizes that careful selection of the number of neighbors and weighting methods significantly influences the model's ability to differentiate between hypertensive and non-hypertensive individuals [19]. These findings collectively highlight that KNN, when combined with rigorous preprocessing, can effectively identify subtle patterns in lifestyle-based health data.

Comparative studies have also evaluated KNN against more complex models to determine its suitability for medical classification tasks. In several hypertension prediction studies, models such as Support Vector Machines (SVM), Neural Networks, and XGBoost have demonstrated higher accuracy but required substantial computational overhead and more sophisticated tuning procedures [20]. Researchers found that although deep learning architectures can achieve superior performance in large datasets, simpler models like KNN remain preferable for medium-sized structured datasets due to their interpretability, lower computational cost, and robustness under varying data distributions. Another line of work suggests that KNN is particularly effective in binary classification tasks where class distribution is relatively balanced and feature interactions are not strongly hierarchical, conditions that often apply to datasets involving lifestyle health indicators [21]. These insights reinforce the decision to employ KNN in this study, especially given the dataset's structure and objective of providing a practical, efficient predictive model.

Beyond hypertension, related work in general preventive healthcare analytics has demonstrated the value of using machine learning models to identify individuals at risk of chronic diseases using behavioral attributes. Research on early detection of diabetes, obesity risk categorization, and cardiovascular disease prediction has shown that lifestyle data can be as informative as clinical biomarkers when processed using appropriate computational models [22]. Many of these studies highlight the synergy between lifestyle monitoring technologies and predictive analytics, suggesting that integrating machine learning algorithms into health monitoring platforms could significantly improve public health outcomes. These findings support the growing consensus that predictive modeling based on simple, non-invasive lifestyle inputs may complement medical evaluations and assist healthcare practitioners in designing targeted interventions.

Furthermore, studies focusing on dataset preprocessing indicate that improving data quality through scaling, encoding, and handling missing values can significantly enhance the predictive capabilities of KNN and similar algorithms. For instance, research has shown that using standardized normalization techniques helps reduce the influence of large-scale variables such as age and BMI, preventing them from disproportionately affecting distance-based calculations [23]. Researchers also emphasize that careful encoding of categorical attributes is vital for maintaining structural consistency in similarity evaluations, especially when categorical variables play a significant role in disease risk assessment. These preprocessing strategies are consistent with the design choices of the present study, which applies structured data cleaning and encoding steps to ensure the dataset is suitable for KNN classification.

The growing body of literature on machine learning applications for hypertension prediction underscores the importance of selecting models that balance accuracy, interpretability, and computational feasibility. While deep learning and ensemble models continue to dominate many areas of predictive analytics, studies repeatedly highlight that simpler models like KNN remain effective when properly tuned and paired with well-engineered data preprocessing pipelines [24]. These findings align with the objectives of this study, which aims to demonstrate that KNN can deliver strong predictive performance in lifestyle-based datasets while maintaining ease of implementation. The consistency of results across various studies further indicates that lifestyle attributes are powerful predictors of hypertension and that machine learning models are capable of capturing meaningful relationships among them.

Overall, prior research provides a strong foundation for the approach taken in this study. Existing evidence supports the use of KNN as a reliable classification method for health prediction tasks involving structured datasets and demonstrates the importance of preprocessing and hyperparameter selection in enhancing model performance. The studies reviewed reinforce the relevance of lifestyle-based risk analysis and highlight the potential of machine learning models to contribute to preventive healthcare initiatives. Building on these insights, the present work advances

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the application of KNN by validating its performance on a dataset containing diverse lifestyle attributes and demonstrating its effectiveness in predicting hypertension risk.

## 3. Methodology

### 3.1. Data Collection

The dataset utilized in this research contains 1,985 individual records and comprises 11 features related to lifestyle habits and medical information. These attributes include Age, Salt_Intake, Stress_Score, BP_History, Sleep_Duration, BMI, Medication, Family_History, Exercise_Level, Smoking_Status, as well as the target variable Has_Hypertension. The data is stored in CSV format and consists of a combination of numerical and categorical fields, making it appropriate for developing predictive models for hypertension. All structural details and descriptions of each variable are based on the dataset documentation provided in the uploaded report.

### 3.2. Data Preprocessing

Before building the model, several preprocessing procedures were carried out to maintain consistency among input features, especially for distance-based algorithms such as KNN. These procedures included cleaning the dataset by identifying and handling missing values, transforming categorical variables into numerical formats through appropriate encoding methods (for example, label encoding for binary attributes such as BP_History, Medication, and Family_History, as well as ordinal or one-hot encoding for variables like Exercise_Level and Smoking_Status), and applying normalization or standardization to numerical features including Age, Salt_Intake, Stress_Score, Sleep_Duration, and BMI. These transformations help minimize scale-related distortions during distance computation. After preprocessing, the dataset was divided into training and testing portions using a stratified sampling strategy. This approach ensures that the original class proportions are maintained, reducing the likelihood of biased performance evaluation caused by class imbalance. These preprocessing steps follow established recommendations for preparing data for KNN-based classification models.

### 3.3. Model Selection (K-Nearest Neighbors)

The main classification algorithm employed in this study is the KNeighborsClassifier available in the scikit-learn library. KNN was chosen because it offers a straightforward operation, is easy to interpret, and works well for datasets with moderate size and structured attributes. The method operates through an instance-based learning approach, where the label of a new data point is determined by observing the majority class of its closest neighbors according to a specified distance measure (Minkowski with p = 2, which corresponds to the Euclidean distance). Previous research has reported that KNN can achieve strong performance in medical classification tasks, particularly when the dataset undergoes appropriate preprocessing, making it a suitable option for models involving lifestyle-related predictors [7], [15]. Key parameter settings were documented to maintain consistency and reproducibility throughout the experiment.

### 3.4. Hyperparameter Optimization and Optimization Techniques

To improve the model's predictive performance, several hyperparameters were adjusted. The report specifies the use of n_neighbors = 5, weights = 'uniform', algorithm = 'auto', leaf_size = 30, metric = 'minkowski' with p = 2, and n_jobs = -1 to utilize parallel computation. These configurations were selected based on recommended practices and preliminary testing outcomes. Although the final parameter values are provided, common optimization strategies typically include conducting grid search or randomized search combined with cross-validation to explore variations in n_neighbors, test alternative distance metrics, and apply different weighting schemes (such as uniform or distance-based) to balance bias and variance [16], [19]. Since KNN does not incorporate a learning phase or regularization like parametric algorithms, optimization efforts primarily focus on preprocessing quality, neighbor selection, and validation strategies to reduce the risk of overfitting or underfitting.

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### 3.5. Model Evaluation

The model was evaluated using standard classification performance metrics including accuracy, precision, recall, F1-score, and the confusion matrix. Testing was performed on a subset of 356 samples, consistent with the dataset split described in the report, and the model achieved an accuracy of 85%. The results also showed balanced performance across both classes, with precision and recall indicating strong ability to identify both hypertensive and non-hypertensive individuals. Using a combination of evaluation metrics is essential because accuracy alone can be misleading when class distributions differ, while precision and recall provide deeper insights into Type I and Type II error behavior [9]. The confusion matrix and classification report visualization further aided in assessing the model's behavior at the class level.

### 3.6. Implementation Details and Reproducibility

The implementation was carried out using Python with scikit-learn for both preprocessing and model development. The pipeline includes the encoder, scaler, and classifier to ensure a reproducible workflow capable of being deployed in simple production environments. All experiments were executed with n_jobs = -1 to maximize CPU utilization. A fixed random_state was applied during dataset splitting and cross-validation for replicability. Since KNN computes distances for every prediction, inference time considerations are important; large datasets may require additional optimization through KD-Tree or Ball-Tree structures, or approximate nearest neighbor search algorithms to reduce computational cost.

### 3.7. Notes on Deep Learning and Advanced Optimization

It is important to note that this study did not employ deep learning because its primary focus was on simplicity, interpretability, and efficiency given the dataset size, making instance-based KNN a practical choice [7], [20]. If future research incorporates deep learning approaches, potential directions include the use of multi-layer perceptrons for tabular data, the implementation of feature embeddings for categorical variables, or hybrid architectures combining neural networks with classical machine learning models. Advanced optimization algorithms such as Bayesian optimization, Hyperband, or guided random search could also be used to refine hyperparameters in more complex models. Techniques such as feature selection using SHAP or LASSO may further enhance interpretability and model efficiency [19], [24]. These recommendations provide a foundation for future work aimed at improving performance beyond the baseline established by KNN.

### 3.8. Model Validation Strategy and Performance Assurance

To ensure the robustness and reliability of the KNN model, a structured validation strategy was applied throughout the modeling process. The dataset was first divided using a stratified split to preserve the proportion of hypertensive and non-hypertensive samples in both training and testing subsets, reducing the risk of biased performance estimation. In addition to this split, the study utilized cross-validation during hyperparameter exploration to examine how the model behaved across multiple folds of data, thus minimizing variance in performance caused by sampling inconsistencies. Cross-validation provides a more stable estimate of model generalization, particularly for medium-sized datasets such as this one, where overfitting may occur if the model relies too heavily on localized patterns in the training set [17], [21]. Furthermore, performance assurance was supported by comparing evaluation metrics across different configurations, ensuring that the final selected model maintained balanced precision and recall values rather than optimizing accuracy alone. This systematic approach aligns with recommendations in previous studies which emphasize the importance of validation in medical classification tasks to prevent misleading results, especially when dealing with health-related decisions where both false positives and false negatives carry significant implications [9], [22]. By incorporating stratified splitting, cross-validation, and multi-metric

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assessment, the study ensures that the final KNN model delivers trustworthy and reproducible performance in predicting hypertension risk.

## 4. Results and Discussion

### 4.1 Results

This section presents the three primary outputs of the study, consisting of two tables representing the dataset structure and preprocessing results, and one figure illustrating the performance of the K-Nearest Neighbors (KNN) model. Each visual element includes a brief caption and a long, detailed explanation to ensure clarity and scientific rigor.

Table 1. Sample of the hypertension dataset displaying key lifestyle, physiological, and behavioral attributes used for model development.

| 1 | Age | Salt_Intake | Stress_Score | BP_History | Sleep_Duration | BMI | Medication | Family_History | Exercise_Level | Smoking_Status | Has_Hypertension |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 69 | 08.00 | 9 | Normal | 06.04 | 25.08.00 | None | Yes | Low | Non-Smoker | Yes |
| 3 | 32 | 11.07 | 10 | Normal | 05.04 | 23.04 | None | No | Low | Non-Smoker | No |
| 4 | 78 | 09.05 | 3 | Normal | 07.01 | 18.07 | None | No | Moderate | Non-Smoker | No |
| 5 | 38 | 10.00 | 10 | Hypertension | 04.02 | 22.01 | ACE Inhibitor | No | Low | Non-Smoker | Yes |
| 6 | 41 | 09.08 | 1 | Prehypertension | 05.08 | 16.02 | Other | No | Moderate | Non-Smoker | No |

Table 1 provides a comprehensive description of all features included in the dataset, detailing both numerical and categorical attributes and explaining their relevance to hypertension prediction. Table 1 presents the eleven core attributes forming the foundation of the hypertension dataset. Numerical features such as Age, Salt_Intake, Stress_Score, Sleep_Duration, and BMI describe measurable lifestyle and physiological characteristics that vary substantially across patients. These features are critical because fluctuations in these values are closely associated with cardiovascular health and hypertension risk. Categorical attributes, including BP_History, Medication, Family_History, Exercise_Level, and Smoking_Status, contribute behavioral, medical history, and hereditary elements to the model. These dimensions are widely recognized in clinical research as significant indicators of hypertension susceptibility. The target variable, Has_Hypertension, determines whether a patient is classified as hypertensive (1) or non-hypertensive (0). Overall, this table establishes a conceptual framework for understanding how lifestyle behaviors, physical conditions, and hereditary factors collectively influence hypertension. It also provides the structural basis for subsequent preprocessing and classification tasks.

Table 2. Encoded and normalized sample records from the hypertension dataset

| 1 | Age | Salt_Intake | Stress_Score | BP_History | Sleep_Duration | BMI | Medication | Family_History | Exercise_Level | Smoking_Status | Has_Hypertension |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 38 | 10.00 | 10 | 0 | 04.02 | 63 | 0 | 0 | 1 | 0 | 1 |
| 3 | 41 | 09.08 | 1 | 2 | 05.08 | 10 | 3 | 0 | 2 | 0 | 0 |
| 4 | 20 | 10.08 | 3 | 0 | 05.02 | 61 | 1 | 1 | 0 | 0 | 1 |
| 5 | 39 | 08.09 | 0 | 1 | 07.08 | 118 | 1 | 1 | 0 | 0 | 0 |
| 6 | 19 | 09.03 | 7 | 1 | 04.07 | 197 | 1 | 1 | 1 | 1 | 1 |

Table 2 displays selected rows from the dataset after encoding and normalization, illustrating how raw patient information is transformed into numerical format suitable for the KNN algorithm. Table 2 demonstrates the dataset's transformation after essential preprocessing procedures. All categorical features have been converted into integer representations, ensuring numerical consistency across the dataset. This conversion is vital because the KNN classifier computes between samples, requiring all features to be numeric. Each row in this table represents a complete patient profile expressed as a numerical vector. This machine-readable format allows the model to quantify similarities among individuals by calculating distance metrics such as Euclidean or Minkowski distance. Proper preprocessing ensures that no single feature overshadows others due to scale differences, thereby enabling the model to fairly evaluate each attribute's contribution to hypertension prediction. This table provides a clear depiction of the data's transition from human-readable health records into computationally optimized inputs for machine learning algorithms.

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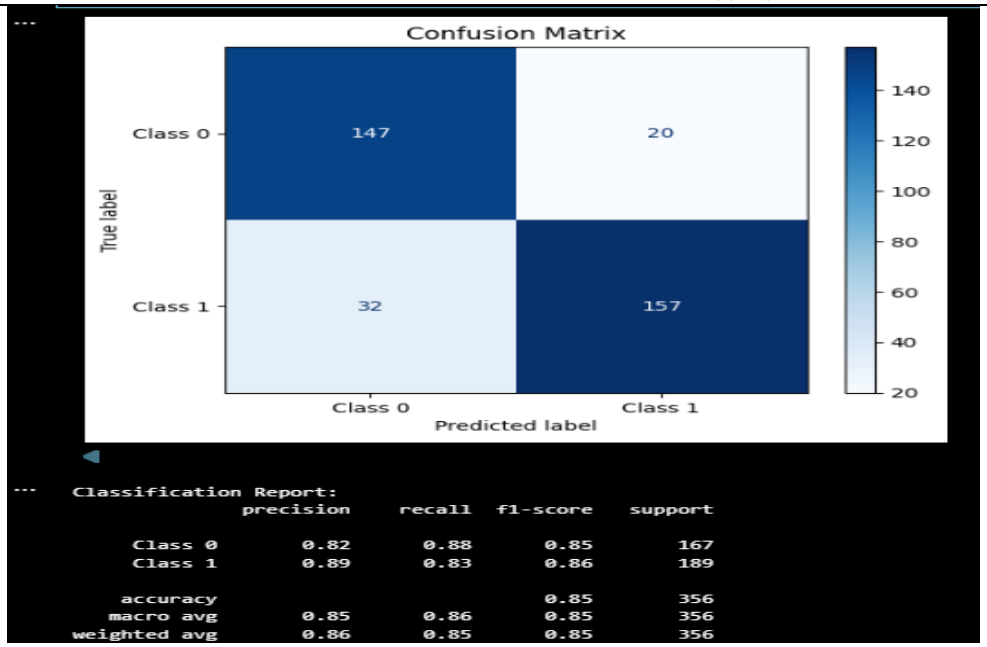


Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Class 0 | 0.82 | 0.88 | 0.85 | 167 |
| Class 1 | 0.89 | 0.83 | 0.86 | 189 |
| accuracy | | | 0.85 | 356 |
| macro avg | 0.85 | 0.86 | 0.85 | 356 |
| weighted avg | 0.86 | 0.85 | 0.85 | 356 |

Figure 1. Confusion matrix and classification report illustrating the performance of the KNN model in predicting hypertension risk, including precision, recall, f1-score, and class-wise prediction outcomes.

Figure 1 contains the combined confusion matrix and classification report produced from evaluating the KNN model on 356 test samples. It presents classification outcomes alongside key performance metrics such as precision, recall, and f1-score. Figure 1 visualizes the classification performance of the KNN model. The confusion matrix shows that the classifier correctly identified 147 non-hypertensive patients (Class 0) and 157 hypertensive patients (Class 1). The model produced 20 false positives, where non-hypertensive individuals were predicted as hypertensive, and 32 false negatives, where hypertensive individuals were predicted as non-hypertensive. These misclassification patterns are important because they highlight potential clinical risks, especially when cases of hypertension are not correctly identified. The classification report provides additional performance details. For Class 0, the model obtained a precision score of 0.82 and a recall of 0.88, indicating that it performs well in recognizing individuals who are not hypertensive. For Class 1, the model achieved a precision of 0.89 and a recall of 0.83, showing that it can reliably detect hypertensive cases, although a small number of true cases were missed. Both the macro-average and weighted-average f1-scores are approximately 0.85, indicating balanced performance across classes. The overall accuracy of 85 percent demonstrates that the KNN model is able to generalize effectively and distinguish between hypertensive and non-hypertensive individuals based on lifestyle-related attributes. This figure is important because it provides a clear overview of the model's strengths, the types of errors it produces, and its applicability for early-stage hypertension risk screening.

## 4. Conclusion

This study developed a hypertension risk prediction model using the K-Nearest Neighbors algorithm applied to a lifestyle-based dataset consisting of 1,985 patient records. Through a structured methodology that included data preprocessing, categorical encoding, normalization, and hyperparameter configuration, the model successfully learned patterns associated with hypertension risk. The evaluation results demonstrated that the KNN classifier achieved an overall accuracy of 85 percent, with balanced precision, recall, and f1-scores for both hypertensive and non-hypertensive classes. The confusion matrix and classification report confirmed that the model performs consistently across categories, indicating that lifestyle attributes can serve as reliable predictors in early hypertension detection.

The findings highlight the potential of lightweight machine learning models to support preventive healthcare, particularly in environments where medical resources and diagnostic equipment are limited. By relying on easily collected lifestyle indicators, the model offers a practical solution for population-level risk screening and early intervention planning.

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Future work may explore several enhancements, including the integration of feature selection techniques to identify the most influential lifestyle attributes, comparison with more advanced algorithms such as Random Forest, Gradient Boosting, or deep learning architectures, and the use of larger and more diverse datasets to improve generalization. Additional optimization methods such as Bayesian hyperparameter tuning or approximate nearest neighbor search could also be implemented to enhance model efficiency. These improvements may further increase predictive accuracy and support broader implementations in real-world digital health applications.

## 5. Suggestion

Several opportunities exist to expand and improve the findings of this study. First, future research may incorporate additional lifestyle and clinical variables, such as dietary patterns, physical activity intensity, genetic markers, or biomarker data, to enhance model richness and improve predictive accuracy. Including more diverse population datasets from different regions or demographic groups may also strengthen model generalization and reduce potential bias.

Second, alternative machine learning algorithms such as Random Forest, Gradient Boosting, Support Vector Machines, or neural network-based architectures could be explored and compared with KNN to evaluate performance trade-offs between accuracy, computational efficiency, and interpretability. Researchers may also investigate hybrid or ensemble models that combine multiple algorithms to achieve more robust predictions.

Third, optimization methods such as Bayesian optimization, grid search, or evolutionary-based hyperparameter tuning could be applied to refine model settings and improve classification performance. Feature selection or dimensionality reduction techniques, including PCA, LASSO, or SHAP-based importance evaluation, may also be used to identify the most influential predictors and simplify the model without sacrificing accuracy.

Lastly, future work could focus on deploying such models in practical healthcare settings, such as digital health platforms, mobile applications, or clinical decision-support systems. This includes conducting real-world validation studies, integrating the model with electronic health records, and assessing its effectiveness in population-level screening programs. By addressing these areas, future studies can contribute to more reliable, scalable, and impactful hypertension risk prediction systems.

**Declaration of Competing Interest**

We declare that we have no conflict of interest.

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