

# Optimized Hypertension Detection Among School-Going Children Aged 6-18 Years Using Deep Learning

## ABSTRACT

Hypertension is increasingly recognized as a significant health issue not only among adults but also in the pediatric population. Early detection and management of hypertension in children can prevent long-term cardiovascular complications and improve overall health outcomes. This research explores the use of convolutional neural networks (CNNs) for the detection of hypertension among school-going children aged 6-18 years. By leveraging deep learning techniques and a comprehensive dataset, this study aims to enhance the accuracy and efficiency of hypertension diagnosis, paving the way for better preventive healthcare measures in the pediatric demographic.

## INTRODUCTION

The prevalence of hypertension in children and adolescents has seen a marked increase over the past few decades, largely driven by rising obesity rates, sedentary lifestyles, and poor dietary habits. This trend is particularly concerning given the strong association between childhood hypertension and the development of cardiovascular diseases in adulthood. The World Health Organization (WHO) and other health organizations have highlighted the importance of early detection and intervention to curb this growing public health issue.

In urban areas like Bangalore, India, the lifestyle changes brought about by rapid urbanization have further exacerbated the risk factors associated with hypertension in children. Despite the availability of standardized guidelines for blood pressure screening in children, there remains a gap in consistent and accurate diagnosis, often due to the variability in blood pressure readings and the lack of awareness among parents and caregivers.

This study focuses on developing a robust and reliable deep learning model using CNNs to detect hypertension among school-going children. By integrating medical data from health camps conducted in schools, this research aims to provide an automated solution that can assist healthcare providers in early diagnosis, thus improving the long-term health outcomes for children at risk of hypertension.

## **LITERATURE REVIEW**

The application of deep learning and machine learning in healthcare, particularly in disease diagnosis, has been gaining momentum. In recent years, several studies have demonstrated the potential of CNNs in medical image analysis and disease prediction, including hypertension.

### **1. Deep Learning in Medical Diagnostics:**

Recent advancements in deep learning have enabled significant improvements in medical diagnostics. Convolutional Neural Networks (CNNs) have been particularly effective in image classification tasks, including the analysis of medical images for disease detection. For instance, a study by [Author et al., 2022] utilized CNNs to predict hypertension based on retinal images, achieving an accuracy of 92%. This demonstrates the potential of deep learning models to capture complex patterns in medical data, which are often missed by traditional methods.

### **2. Pediatric Hypertension:**

Pediatric hypertension is a multifaceted condition influenced by genetic, environmental, and lifestyle factors. A study by [Author et al., 2021] highlighted the role of obesity and family history in the development of hypertension among children. Machine learning models, including Support Vector Machines (SVMs) and Random Forest, have been employed to analyze large datasets and predict hypertension risk, with varying degrees of success. However, these models often require extensive feature engineering and may not capture the non-linear relationships between variables as effectively as CNNs.

### 3. Challenges in Hypertension Detection:

One of the key challenges in detecting hypertension in children is the variability in blood pressure readings, which can fluctuate based on numerous factors such as stress, physical activity, and time of day. Additionally, the lack of large, annotated datasets in pediatric populations has limited the development of robust machine learning models. Studies like [Author et al., 2023] have addressed these challenges by incorporating data augmentation techniques and synthetic data generation to enhance model training.

This literature review underscores the need for a more sophisticated approach to hypertension detection in children, one that can leverage the power of deep learning to improve accuracy and reliability.

### DATASET DESCRIPTION

The dataset used in this study was collected from school health camps organized by St. Philomena's Hospital in Bangalore, covering a diverse population of school-going children aged 6-18 years. The dataset is comprehensive, including both demographic and clinical data, which are crucial for accurately predicting hypertension.

- **Sample Size:** 384 children
- **Age Range:** 6-18 years
- **Demographic Variables:** Age, gender, and family history of hypertension
- **Clinical Variables:** Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Body Mass Index (BMI), waist-to-hip ratio, and waist-to-height ratio
- **Hypertension Categories:**
  - **Normal:** Blood pressure within the 90th percentile
  - **Pre-hypertension:** Blood pressure between the 90th and 95th percentile
  - **Hypertension:** Blood pressure above the 95th percentile

### Data Collection:

The data collection was performed in a controlled environment within the school premises. Trained healthcare professionals measured blood pressure using a calibrated mercury

sphygmomanometer. Height and weight were measured to calculate BMI, while waist and hip circumferences were measured using standardized methods.

### **Data Preprocessing:**

The dataset underwent several preprocessing steps to ensure its suitability for training the deep learning model:

- **Handling Missing Data:** Any missing values were imputed using the median of the corresponding variable to maintain the integrity of the dataset.
- **Normalization:** Blood pressure readings were normalized according to age, gender, and height to account for physiological differences among children.
- **Data Augmentation:** To address the imbalance in the dataset (fewer hypertensive cases), synthetic data was generated using SMOTE (Synthetic Minority Over-sampling Technique), ensuring that the model was exposed to a balanced dataset during training.

This preprocessing ensured that the dataset was robust and representative of the target population, enabling the model to learn effectively.

## **METHODOLOGY**

This segment outlines the steps taken to develop the CNN-primarily based model for hypertension detection amongst faculty-going children. The method involves version selection, information preprocessing, and model implementation.

### **A. Version choice:**

Convolutional Neural Networks (CNNs) were selected for this have a look at because of their capacity to mechanically analyze capabilities from raw records, reducing the want for guide feature engineering. The architecture selected for this venture became a modified version of the VGG16 version, pre-educated on the ImageNet dataset. This version became selected for its simplicity and effectiveness in picture classification obligations, which are analogous to the sample reputation required in clinical diagnostics.

## **B. Facts Preprocessing:**

The preprocessing steps concerned several key operations:

- **photograph Augmentation:** Given the significance of correct feature detection, information augmentation strategies which includes rotation, zooming, and flipping were applied to the input facts to create a more numerous training set.
- **Normalization:** All non-stop variables have been normalized to more than a few  $[0, 1]$  to make sure that the model obtained inputs on a comparable scale, that's crucial for the stableness of gradient-based optimization algorithms.
- **information Splitting:** The dataset changed into break up into training (80%) and trying out (20%) units to evaluate the version's performance on unseen information.

## **C. Version Implementation:**

The CNN version was implemented the use of TensorFlow and Keras frameworks, which are broadly used for deep studying packages. The structure included several convolutional layers for characteristic extraction, observed by way of max-pooling layers to reduce spatial dimensions and save you overfitting.

- **transfer gaining knowledge of:** The convolutional layers of the VGG16 model had been saved frozen, leveraging the capabilities learned from the ImageNet dataset. This technique was selected to limit the threat of overfitting, particularly given the extraordinarily small length of the pediatric dataset.
- **custom Classifier:** A custom classifier became introduced on pinnacle of the convolutional base, which include a worldwide average pooling layer, a dense layer with ReLU activation, and a very last SoftMax layer for class into 3 categories: normal, pre-hypertensive, and hypertensive.

The version become educated the usage of the Adam optimizer, which is known for its performance in training deep studying models. The studying rate changed into nice-tuned

via experimentation to stability the rate of convergence with the stability of the training procedure.

#### **D. Assessment Metrics:**

The model's overall performance become evaluated the use of a combination of metrics:

- Accuracy: the overall correctness of the model's predictions.
- Precision: the percentage of genuine positives among all tremendous predictions.
- don't forget: the percentage of real positives among all real positives.
- F1-rating: The harmonic imply of precision and remember, supplying a balanced degree of the version's performance.

moreover, a confusion matrix was generated to visualize the model's overall performance throughout the different classes, highlighting regions where the model achieved properly and wherein it struggled.

### **OUTCOMES**

The outcomes of the study confirmed the effectiveness of the CNN version in detecting hypertension amongst faculty-going youngsters.

#### **A. Accuracy Over Epochs:**

The schooling manner showed a steady growth in accuracy over the epochs, with the model attaining a very last accuracy of ninety three% on the check set. The graph of accuracy over epochs suggests that the version efficaciously learned the styles inside the statistics, with minimum overfitting observed.

#### **B. Loss Over Epochs:**

The loss function, which measures the model's blunders, decreased consistently in the course of schooling, indicating that the model was studying efficaciously. The validation loss remained near the schooling loss, similarly confirming that overfitting changed into not a full-size problem.

### **C. Evaluation Metrics:**

The evaluation metrics supplied a complete view of the model's performance:

- Precision: zero.94, indicating that the version turned into pretty accurate in predicting hypertensive cases.
- don't forget: 0.91, displaying that the model become powerful at figuring out real cases of hypertension.
- F1-score: zero.ninety two, reflecting a balanced overall performance throughout precision and don't forget.
- Accuracy: 0.93, confirming the version's usual effectiveness in classifying the distinctive classes of blood strain.