**A**

**PROJECT REPORT**

**ON**

# "HYPERTENSION DETECTION USING TIME-SERIES IMAGE MODALITIES AND CONVOLUTIONAL NEURAL NETWORK"

Submitted in

Partial Fulfillment of the requirement

For the degree of

**BACHELOR OF TECHNOLIGY**

**IN**

**ELECTRONICS ENGINEERING**


**DEPARTMENT OF ELECTRONICS ENGINEERING**

**RAJKIYA ENGINEERING COLLEGE, KANNAUJ**


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**Under the supervision of**

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**DEPT.OF ELECTRONICS ENGINEERING**

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# DECLARATION

I hereby to declare that the project report entitled - "**Hypertension Detection Using Time-Series Image Modalities And Convolutional Neural Network**", which is being submitted for the fulfilment ofthe B.Tech Degree in Electronics Engineering to Rajkiya Engineering College, Kannauj (UP) is an authentic record of my genuine work done under the guidance of Our Mentor Mr. Gaurish Joshi, Department of Electronics Engineering, Rajkiya Engineering College, Kannauj.

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# CERTIFICATE

This is certified that the project entitled "**Hypertension Detection Using Time-Series Image Modalities And Convolutional Neural Network**", is submitted by Anand Vishwakarma, Ankur Awasthi, Apoorv Srivastava and Arju Katiyar in the partial fulfillment of the award of degree of B.Tech in Electronics Engineering of **Dr. A.P.J Abdul Kalam Technical University**, is a record student own work carried under our supervision and guidance'. The project report embodies result of original work and studies out by student and the content do not from the award of any other degree to the candidate or to anybody else.

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# ACKNOWLEDGEMENT

We are delighted to announce the successful completion and submission of our project report, which is a mandatory part of the Electronics Engineering Bachelor of Technology curriculum.

We would like to express our sincere appreciation to Dr. Rachna Asthana, the Director of RAJKIYA ENGINEERING COLLEGE KANNAUJ, for providing us with the necessary resources and continuous support. Our gratitude also goes to Dr. Arun Kumar Singh (H.O.D) Electronics Engineering Department, for his guidance and valuable recommendations during the project preparation.

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# ABSTRACT

Hypertension (HPT) is a medical condition characterized by high blood pressure, which can manifest through symptoms such as headaches, dizziness, and fainting, and potentially lead to severe diseases affecting the heart, kidneys, or brain. Traditional detection and monitoring methods using a sphygmomanometer are often labor-intensive and inconvenient. Recently, ballistocardiogram (BCG) signals, which capture the heart's mechanical vibrations, have been employed for HPT detection. In this study, we introduce a fully automated HPT detection system that leverages time-series modalities and a convolutional neural network (CNN) for precise detection of HPT using BCG signals. Our methodology involves converting raw BCG data into four types of images: Gramian Angular Field (GAF), Recurrence Plot (RP), Markov Transition Field (MTF), and a composed image that integrates these three imaging modalities. These images are then processed using a benchmarked ResNet50 model, AlexNet model and Hpt-Net, a deep learning model specially designed for detection of hypertension. Compared to Res-Net50 and AlexNet, Hpt-Net model requires fewer learnable parameters, resulting in faster and more efficient computation. This indicates that Hpt-Net model is performed well with composed image modalities with an accuracy of 98.3%. Experimental results shows an utilizing BCG signals from a public dataset demonstrate the effectiveness of our technique for automated hypertension detection.

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# CHAPTER 1
# INTRODUCTION

## 1.1 Motivation and Objective

Hypertension (HPT) is a significant cause of cardiovascular complications and high mortality rates globally. Traditional methods for detecting and monitoring hypertension, such as using a sphygmomanometer, are labor-intensive, time-consuming, and not practical for long-term monitoring. Continuous and accurate measurement of blood pressure (BP) is essential for diagnosing the severity of HPT, but traditional methods fall short in this regard. Ballistocardiography (BCG), which measures the ballistic force generated by heart movements, offers a promising alternative due to its ability to provide distribution measurements with minimal load and promptly reflect blood pressure readings. BCG signals, being multivariate time signals, capture critical cardiac cycle information that can be leveraged for HPT detection.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have shown great potential in continuously monitoring and managing hypertension using various physiological signals. However, existing methods using electrocardiography (ECG), photoplethysmography (PPG), and heart rate variability (HRV) signals involve complex feature extraction processes and require significant manual effort and tuning. Moreover, these methods are often sophisticated, noisy, costly, and may lack privacy. Therefore, there is a need for a simpler, more efficient, and automated approach to detect HPT using BCG signals.

## 1.2 Previous work

For BCG recording, a sensor is directly placed inside the mattress or bed where one sleeps or sits [1]. Long-term recording of blood pressure (BP) is required to diagnose the severity of HPT, which is not possible using a traditional mercury-based sphygmomanometer, as it is very time-consuming [2]. For long-term BP recording, a simple and accurate system is required.

Nowadays, researchers have presented various artificial intelligence (AI)-based approaches for continuous monitoring, management, and classification of HPT with other health complications using different physiological signals. For example, in [3], authors demonstrated the utility of a machine learning (ML) algorithm for predicting HPT using anthropometric measurements. Fan et al. [4] utilized a deep learning model with fundus images to detect primary open-angle glaucoma. Mazza et al. [5] addressed the use of ML techniques for BP management in the acute phase of ischemic stroke. Tan et al. [6] designed a lightweight AI-enhanced BP monitoring wristband for continuous BP monitoring. The prediction error of their proposed model is less than 4 mmHg. In [7], the authors developed a triboelectric sensor and a deep learning-based model for continuous BP monitoring. Their model produces a mean absolute deviation of 3.79 ± 5.27 mmHg in measuring systolic BP and 3.86 ± 5.18 mmHg in measuring diastolic BP.

Yousefian et al. [8] investigated the potential of BCG to compute BP value using PTT. They

In [9], authors reviewed the clinician-centric approach to AI and ML employed for medicine and HPT. Various applications of AI for HPT prediction and management have been reviewed in [10]. In [11], authors examined the application of various emerging technologies to detect and manage HPT in the general population as well as special population groups such as pregnant women, patients with atrial fibrillation, children, and elderly people.

Authors in [12] employed a combination of continuous wavelet transform (CWT) and deep learning techniques to detect HPT from PPG signals. Their proposed system obtained an accuracy of 90%. An ensemble learning-based HPT prediction model developed by Fitryani et al. [13] attained a classification accuracy of 76% in classifying normal and HPT classes. A zero-effort technique was used to monitor BP by Chang et al. [14]. Melilo et al. [15] used a combination of traditional ML algorithms with a CNN model and identified HPT patients with an accuracy of 87.8%. Author in [16] employing Gabor transform, smoothed pseudo-Wigner Ville distribution, and short-time Fourier transform, T-F spectral images are generated and fed into the proposed CNN (Hyp-Net), achieving accuracy of 97.65% in HPT detection [22].

### 1.3 Brief Introduction of our work

In our work we are trying to automate the hypertension detection using time series image modalities and Convolutional Neural Network (CNN). For that we first apply Z-score normalization on the BCG Signal consist of Hypertension and Normal classes after that we segmented the signal 30 sec with sampling rate of 100 Hz. Segmented signal are now apply with time-series image encoding transform Recurrent Plot (RP), Markov Transition field (MTF), Gramian Angular Field (GAF) and Composed image formed by integrating the previous three image modality transform. Now the encoded images are used for training of pre-trained deep learning model ResNet50, AlexNet and our proposed model Hpt-Net. After training above three model can be used for detection of Hypertension.

# CHAPTER 2
# METHODOLOGY

The method involves acquiring BCG data, Z-Score normalization, segmentation technique and signal to enoded image by using time series transformation technique. Three transformation techniques namely GAF, MTF, RP are employed to obtain time-series encoded images and there three types of images are integrated in order to formed composed images. These images are fed to two pre-trained CNN models and proposed Hpt-Net for the automated detection of HPT BCG signals. A detailed description of each step of the proposed method is given by :

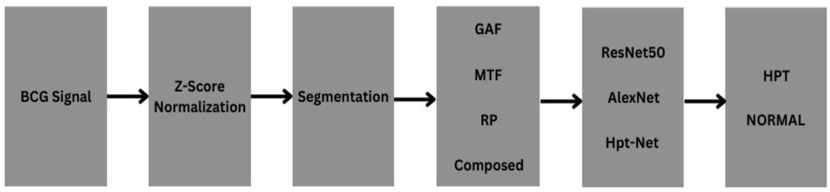



Fig 1. Proposed Methodology

## 2.1 Dataset:

The BCG (Ballistocardiogram) signal is a non-stationary physiological signal representing micro-body vibrations resulting from the heart's mechanical activity. These vibrations are significantly influenced by blood pressure [18]. The RS-611 sensor, a government-approved medical device, detects these micro-body movements. For BCG recording, a micro-movement sensitive mattress, an analog to digital converter (ADC), and a PC terminal are employed. The dataset comprises 67 records (35 males and 32 females) of normal BCG signals and 61 records (23 males and 38 females) of hypertensive BCG signals [19]. Each BCG signal is sampled at 100 samples per second with a 16-bit ADC resolution. Blood pressure (BP) for each subject is measured in four consecutive sessions over three weeks, with the average values determining the final systolic (SBP) and diastolic (DBP) blood pressure readings. Subjects with BP readings over 140/90 mmHg are classified as hypertensive (HPT), while those with lower readings are considered normal. Details of the database are available in [19] . The BCG signals are normalized using the Z-score method to account for variations in body weight. The J-peak of the BCG signal effectively indicates heart rate fluctuations due to sudden changes in blood pressure.

## 2.2 Z-Score Normalization:

The amplitude of the BCG signal is influenced by body weight, so signal normalization is employed to mitigate amplitude discrepancies caused by varying body weights. The Z-score method is utilized for this purpose, calculated as follows:

$$X_k = \frac{x_k - \mu}{\sigma} \tag{1}$$

Where $x_k$ is the kth value of the input, μ is the mean, and σ is the standard deviation of the input BCG signal. $X_k$ represents the normalized BCG signal of $x_k$ [20]. In this study, each BCG record is normalized using the Z-score method respectively. Fig 2. and Fig 3. shows normal and HPT original and normalized signal respectively.

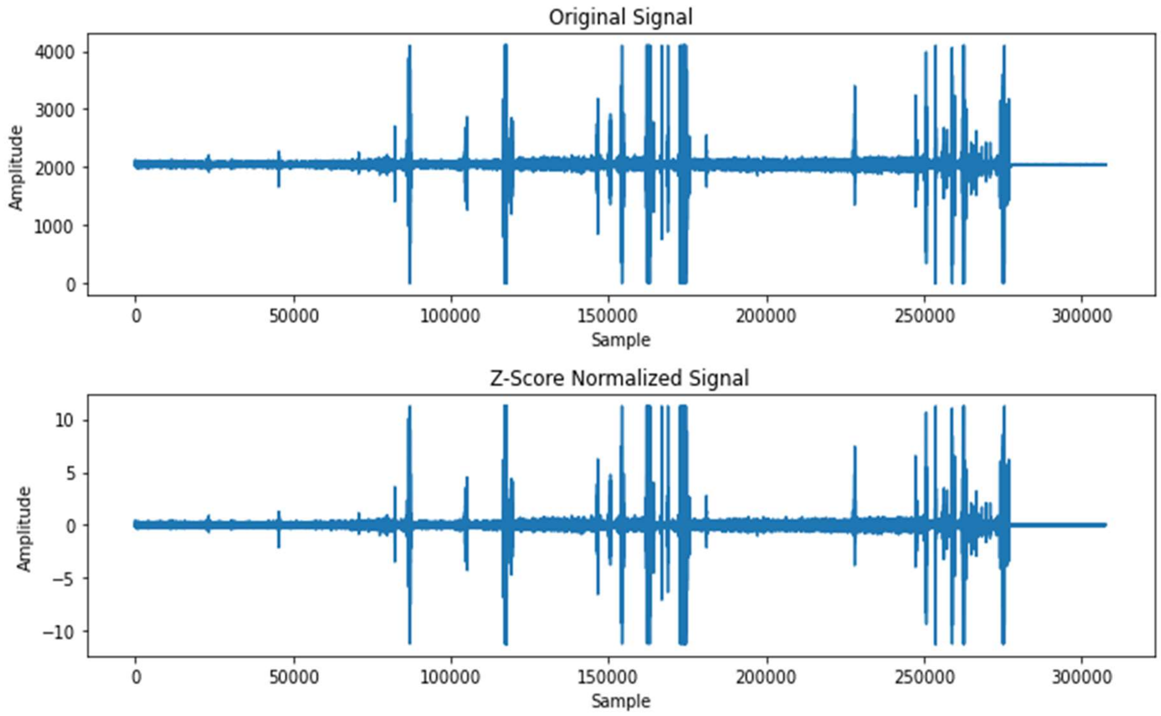



Fig 2. Original vs Normalized BCG signal of Normal Person

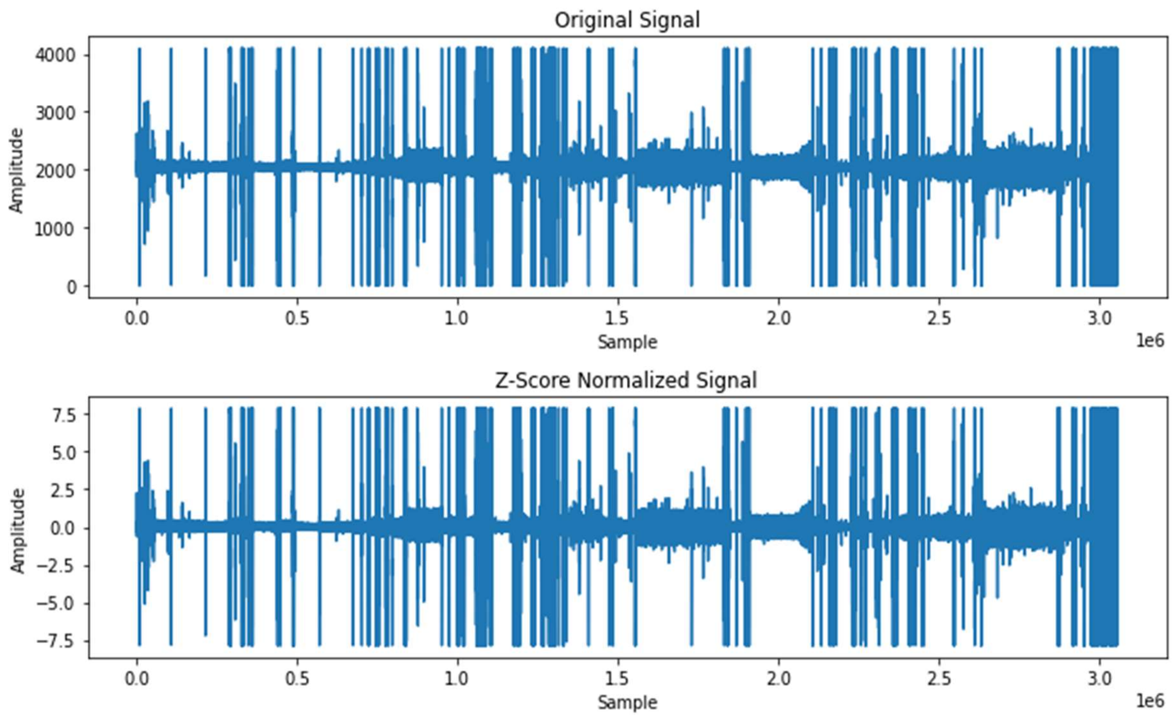



Fig 3. Original vs Normalized BCG signal of HPT Person

**2.3 Segmentation:**

The normalized BCG signal was sampled at a frequency of 100 Hz to capture optimal waveforms. The extensive 13-hour BCG recordings from the study were divided into 30-second segments. This resulted in 61,525 segments for the HPT class and 71,413 segments for the HC class. In total, 132,938 BCG signal segments were analyzed for both HC and HPT categories [20].

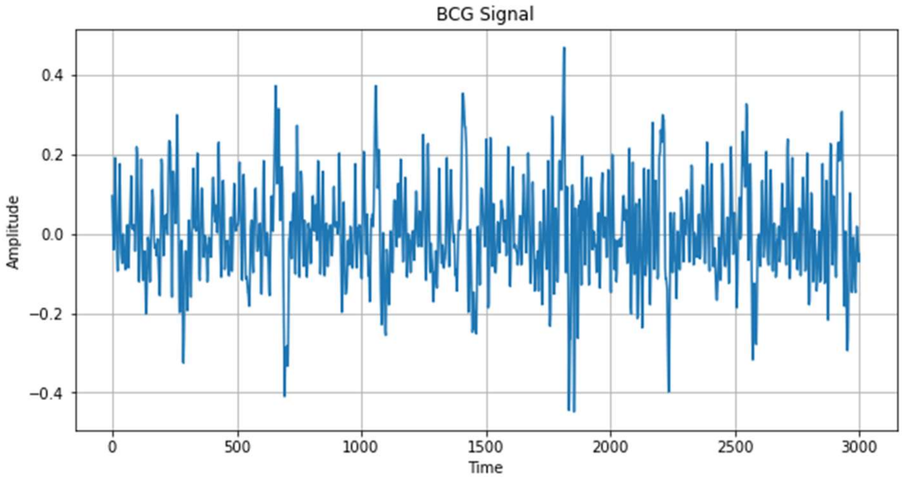


Fig 4. Segmented HPT BCG Signal

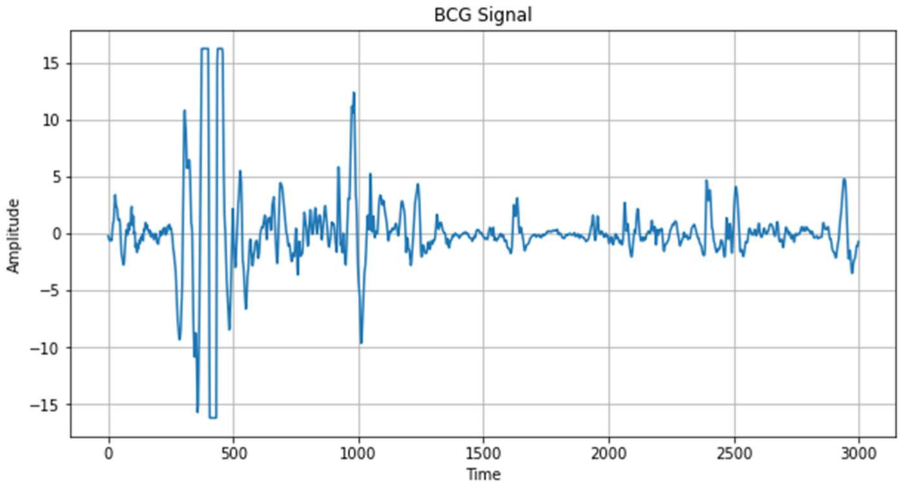


Fig 5. Segmented Normal BCG Signal

### 2.4 Signal Transform:

Since BCG signal is a non-stationary in nature so there is no direct transform for non periodic for that reason we need other methods signal for image formation. We transform the input heart-beats into three types of images called GAF, RP and MTF images and also form Composed image by integrating above three transforms. A brief introduction of these transforms are given as [21]:

**A. Formation of Images By Recurrence Plot (RP):**

A recurrent plot (RP) is a visualization technique used to analyze time series data, especially data that exhibits repeating patterns over time. It reveals recurrent patterns in a time series by plotting points where similar states occur close together diagonally. There are four step involve in whole image formation. At first, we segment the whole time series signal in short interval knowns as epochs. after segmentation from each segment relevant features are extracted. now every segment feature is correlate with itself and other segmented feature base on the correlation a threshold value is selected after setting the threshold value final time vs time plot are formed by using dot plotting in that plotting if the correlation is higher than the threshold value that means both segment are similar in terms of feature than dot in plot are dark based correlated value .If correlated value is less than threshold value than both segment has less similarity than the plot are light based on the correlated value.

$$R_{ij} = \alpha(\delta - \|s(i) - s(j)\|) \quad (2)$$

where $\delta$ is threshold and α is the heavyside function.

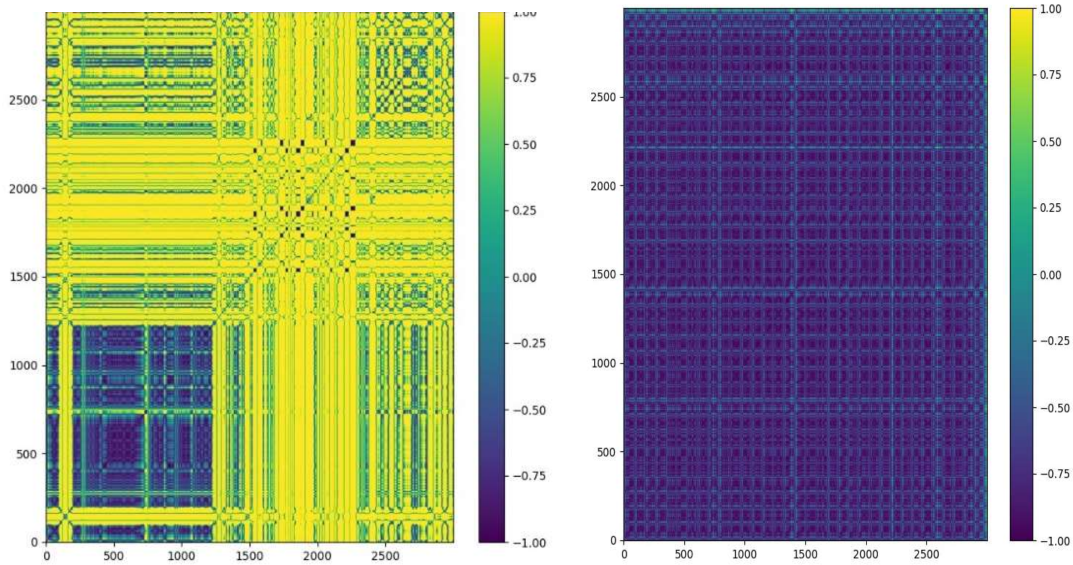



Fig 6. Normal vs HPT RP image modalities

**B. Image Formation using Markov Transition Field (MTF):**

A Markov Transition Field plot is among the specific technique which can encode the image in time vs time plot from time series plot. It takes a sequence of data points (like an BCG signal) and transforms it into a visual representation that captures the probabilities of transitioning between different states in that sequence. It represents the probabilities of transition between different states in the data over time. This method is based on the concept of Markov chain, which define the probability of transitioning to the next state depends only on the current state not on previous state. For converting the MTF image from time series plot, the range of the time series plot is divided in small segments (discrete) which are known as the Bins[$\omega_i$]. Each bin has assigned valued based on the magnitude. MTF plot describe the likelihood of transitioning between states in your data. If two data segments hold similar patterns, there's a higher chance of them transitioning through similar state sequences over time. Each bin is correlated with each bin and all correlated values [$\omega_{i_j}$] are store in a square matrix called transition matrix where [$\omega_{i_j}$] represent probability of consecutive value going from bin i to j. if two bn hold similar value than the probability of transition will be higher that hold the darker colour in plot while lighter colour represent lower probabilities of transitions.

$$pij = P(Xt+1 = j \mid Xt = i) \tag{3}$$

Calculates the probability of transitioning from one state (bin) i to another state (bin) j. This formula is the foundation for constructing the MTF.

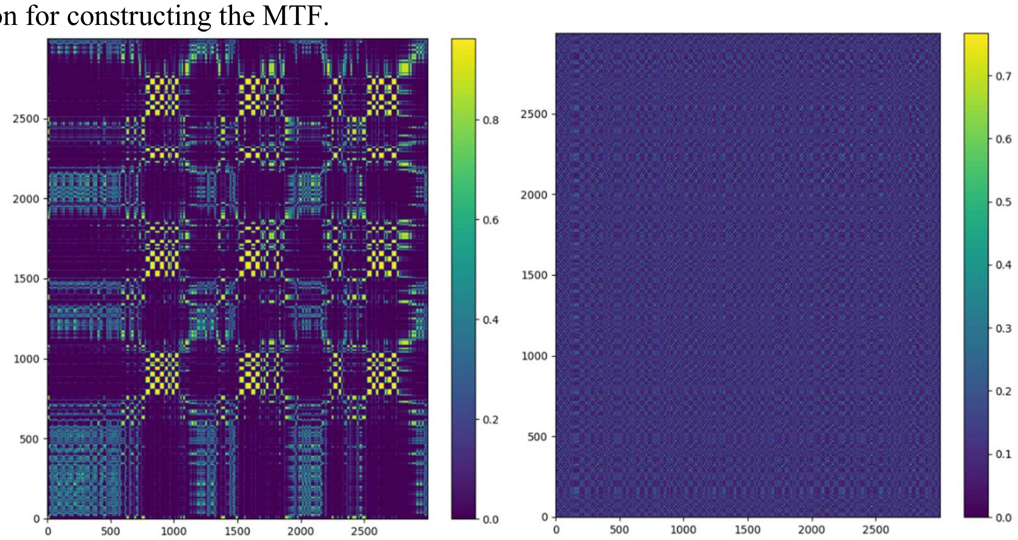



Fig 7. Normal vs HPT MTF image modalities

**C. Image Formation using Gramian angular field (GAF):**

Gramian Angular Field is very specific method for displaying a time series plot as a visual image it shows the temporal correlations between various data segment based on the similarity in polar angle. This encoding method involves four steps. According to this method at first the time series signal is segment in small segment and every segment is convert to the polar(r,$\theta$) form cartesian plot (x= time, y= amplitude). This polar form contains principal argument that argument contains main feature of image based on the direction. Based on similarity between the angles of each segment we construct the Gramian matrix these similarities can be measured in two forms. One is in form of summation field, here the matrix stores the value of the cosine of the difference between the principal angle of two segment. As we know, for principal argument cos is decreasing function. If the segment has high similar value than the difference of angles is very low. For low angle cosine provide the higher value. So for the high value in matrix show the great similarity. Another method is Gramian Angular difference field, this method describes the absolute difference between the principal angle. If the angle has higher similar value than segment has high similarity, else the matrix has high value than that segment has less similarity that means smaller value represent higher similarity.

$$\text{Gramian field} = \text{Cos}(\beta_i - \beta_j) \tag{4}$$

$$\beta = \arccos(sk0)$$

Where β is principal argument, sk0 is the normalized amplitude of sample.

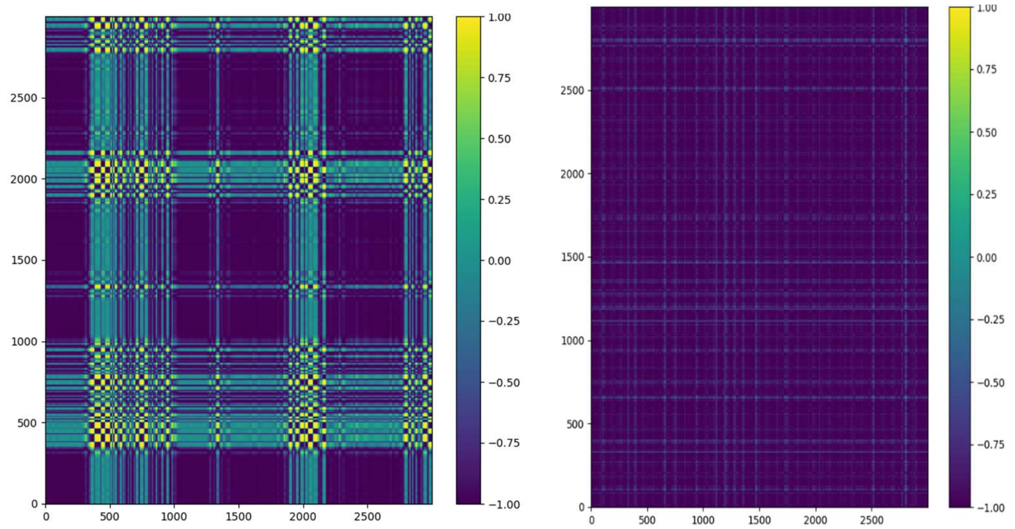


Fig 8. Normal vs HPT GAF image modalities

**D. Composed Image:**

This method provide temporal feature of time series plot but these feature are not enough for detection of hypertension accurately So, to overcome this problem we need a new image modality which contain such a feature which provide us more accuracy. The reason for selecting GAF, MTF, and RP is that they are three distinct statistical techniques for converting BCG data into pictures. They are lossless transformations because they maintain the temporal information as they are being transformed. These three grayscale pictures are combined to create a triple channel image (GAF-RP-MTF). GAF, RP, and MTF images are regarded as three orthogonal channels, or three distinct colours in RGB image space, when analyzing a coloured image. This is known as a triple channel image.

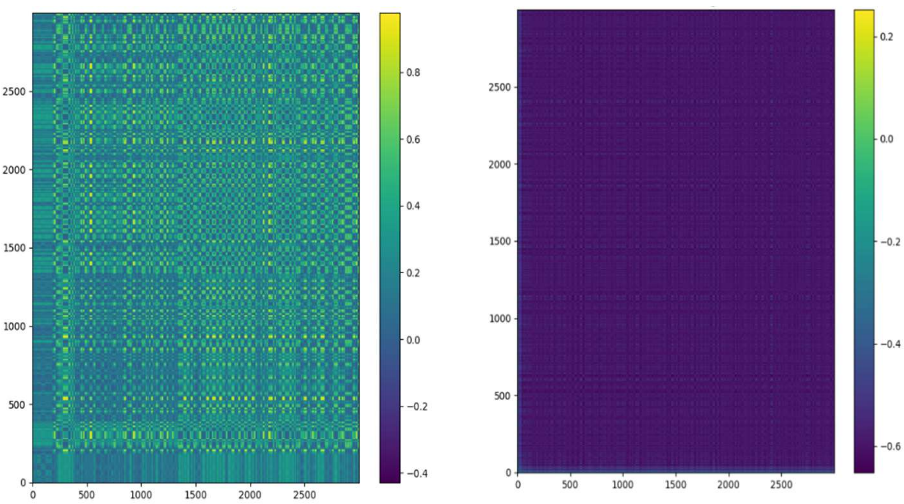


Fig 9. Normal vs HPT Composed image

**2.5 Convolutional Neural Network:**

Convolutional Neural Networks (CNNs) are a significant type of deep neural network that utilize the convolutional operation rather than traditional matrix multiplication for input processing. This characteristic enables CNNs to effectively identify and differentiate various features across different classes. CNNs have shown remarkable performance in medical applications, especially in tasks related to identification and classification. Recent developments in CNN technology have led to the adoption of various pre-trained deep CNN models for a wide range of biomedical applications. Noteworthy examples include SqueezeNet, AlexNet, VGG16, and GoogleNet. In this research, we employ two well-known CNN models, AlexNet and ResNet50, for HPT classification. The ResNet50 model, developed by He et al.[22] , achieved first place in the ILSVRC 2015 for classification, recognition, and segmentation tasks.

This article presents a new deep neural architecture designed to enhance spectral classification accuracy. Our newly developed and configurable Hpt-Net model achieves the highest classification accuracy in this study. Figure 9 illustrates the block diagram of the proposed Hpt-Net. The architecture includes an input layer, three convolutional layers (CL) with rectified linear unit (ReLU) activation, three pooling layers (PL), a sigmoid layer, a dropout layer, a fully connected (FC) network, and an output classification layer. Various image modalities derived from the discussed methods are fed into Hpt-Net's input layer. The convolutional layers extract a subset of highly discriminative features from the input image using a set of convolutional kernels, which are smaller than the input image dimensions. These kernels traverse the image, computing the output via convolution [23].

$$P*Q = \sum M(i,j)Q(x+i,y+j) \quad (5)$$

Rectifier-Linear unit (Re-LU) is the most frequently used activation function in the CNN model [24]. It is given as:

$$\mathrm{ReLU}(x) = \max(0, x) \quad (6)$$

The sigmoid layer is particularly important as it introduces non-linearity into the model, enabling it to handle complex patterns by squashing the input values to a range between 0 and 1, which is especially useful for binary classification tasks.

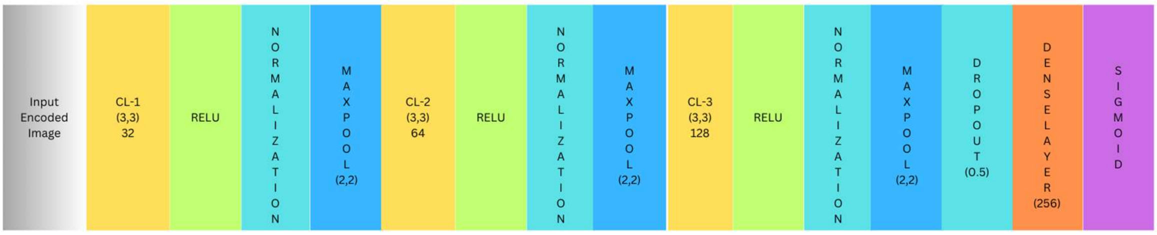



Fig 10. Proposed Architecture for Hpt-Net

# CHAPTER – 3

# EXPERIMENTAL ANALYSIS AND RESULT

## 3.1 System Configuration:

Hypertension detection system was developed using a system configuration optimized for efficient data generation, version control and code execution. The following system setup was employed to facilitate the project:

**1. Hardware Specifications:**

**a)** CPU: Intel Core i5 or higher (quad-core or higher recommended)
**b**) RAM: 8GB or higher
**c)** Storage: SSD for fast data access

**2. Software Specifications:**

**a)** Operating System: Windows
**b**) Integrated Development Enviroment (IDE): Kaggle with Jupyter Notebook Support
**c)** Version Control: Git for code versioning and collaboration

**3. GPU and Code Execution:**

**a)** GPU Execution: Kaggle was utilized for code execution due to absence dedicated GPU at local system
**b**) T4 GPU: The remote setup in Kaggle allowed the utilization of powerful T4 GPU, enabling accelerated model training and evolution.

**4. Python Enviroment and Libraries:**

**a)** Python Version : Python 3.7 or higher
**b**) Libraries : Pandas, NumPy, Matplotlib, Scikit-learn, Tensorflow, Keras

**5. Deep Learning Model Development:**

**a)** Jupyter Notebook in Kaggle : Jupyter Notebook integration with Kaggle allowed for seamless development and experimentation.
**b**) Model Architecture : ResNet50 and Hpt-Net
**c)** Layers : Conv2D, MaxPooling2D, Flatten, Dense, Dropout
**d)** Optimizer : Adam
**e)** Loss Function : Binary Cross Entropy

## 3.2 Result:

Traditional hand-crafted machine learning (ML) techniques for hypertension (HPT) detection require extensive signal pre-processing, making the process cumbersome and prone to suboptimal performance due to dependency on feature selection and classifier choice [1]. To address these issues, we propose the Hpt-Net model, a deep learning-based approach that automates feature extraction and HPT detection. In our study, we trained and validated the models over 20 epochs, dividing the dataset into eight parts for training, one part for validation, and one part for testing for each image modality. the learning rate of each weight is optimized by the Adam optimizer with the initial learning rate of 10—04, the drop-out value of 0.5, and a validation frequency of 10 is chosen with 32 batch sizes for proper model training our experimental results showed that Hpt-Net significantly outperformed ResNet50 in detecting hypertension from BCG signals. The composed images, which integrate Recurrence Plot (RP), Markov Transition Field (MTF), and Gramian Angular Field (GAF) transformations, provided a richer feature set compared to individual transformations, thereby enhancing classification performance. Detailed results are presented in Table 1.

**Table 1:** Accuracy comparison of image modalities

| Modalities | Res-Net50 | AlexNet | Hpt-Net |
|---|---|---|---|
| **RP** | 87.03 | 93.15 | 95.80 |
| **GAF** | 85.98 | 89.09 | 91.03 |
| **MTF** | 86.03 | 90.11 | 93.77 |
| **Composed** | 87.50 | 96.66 | 98.33 |

The highest accuracy is obtained using Composed images. The developed Hpt-Net model is able to extract more significant information from composed images. The accuracy and loss graphs obtained using composed images each each iteration using Hpt-Net, ResNet50 and AlexNet are shown in Fig 11. , Fig 12. And Fig 13. respectively.

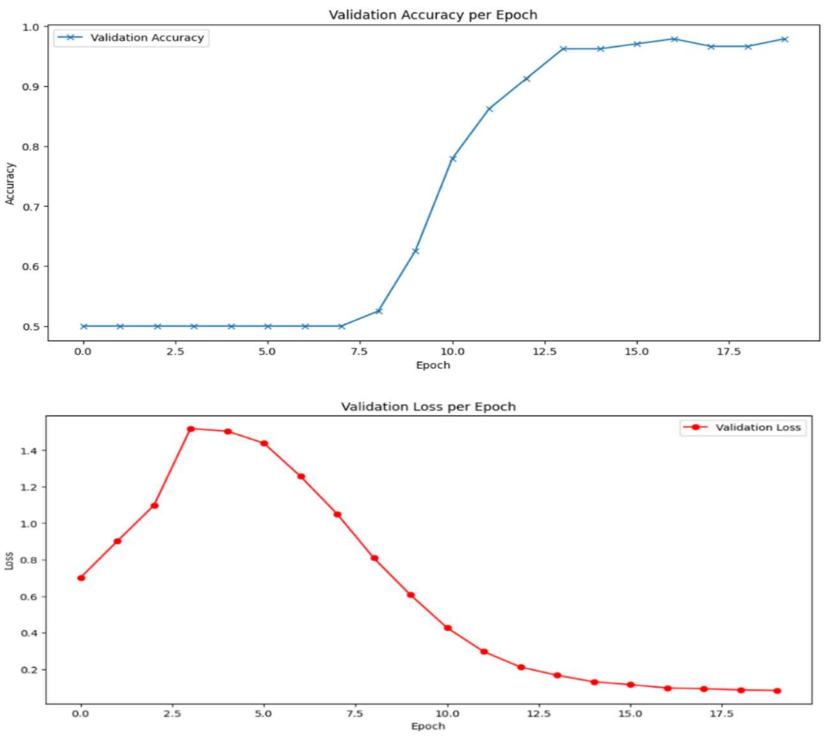



Fig 11. Accuracy and Loss Plot for Composed image on Hpt-Net

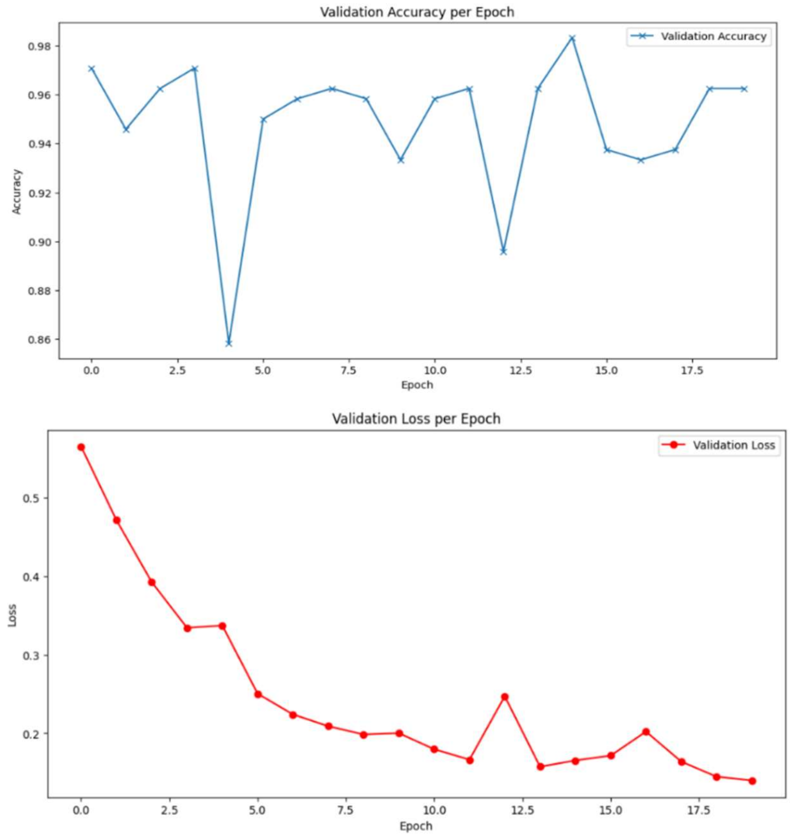



Fig 12. Accuracy and Loss Plot for Composed image on ResNet50

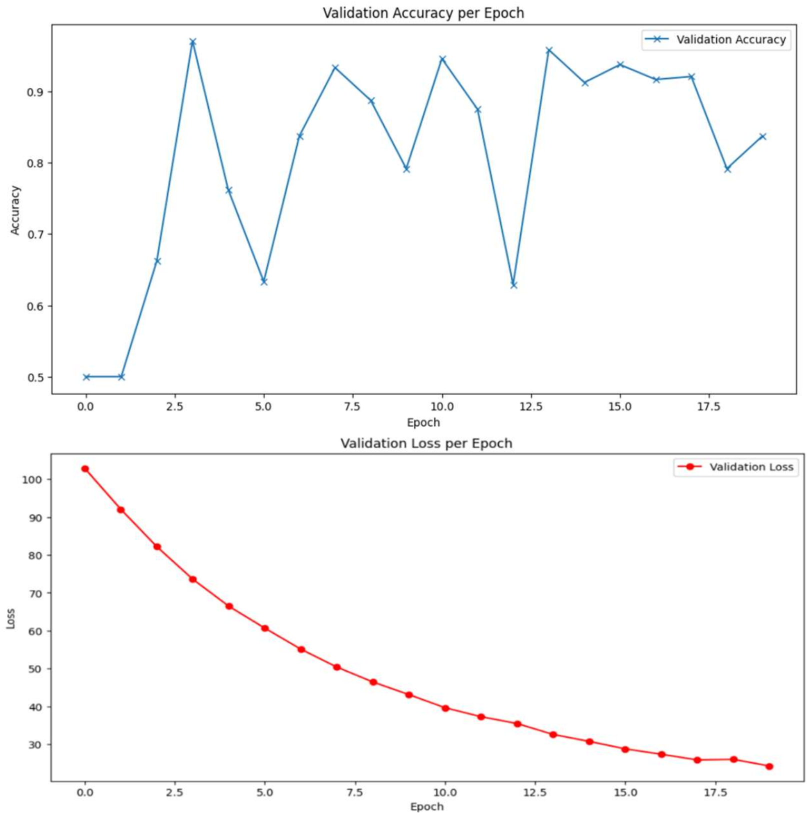



Fig 13. Accuracy and Loss Plot for Composed image on Alex-Net

The integration of RP, MTF, and GAF transformations into composed images contributed to a richer feature set, thereby enhancing the model's classification capabilities. The detailed comparison of the performance metrics for ResNet50 and Hpt-Net is presented in Table 2.

**Table 2**: Performance Metrics Comparison

| Parameters | ResNet50 | AlexNet | Hpt-Net |
|---|---|---|---|
| **Accuracy** | 88 | 97 | 98 |
| **Precision** | 89 | 94 | 100 |
| **Recall** | 85 | 93 | 97 |
| **F1 Score** | 87 | 97 | 98 |

The confusion matrix obtained for the automated detection of HPT using Hpt-Net with composed images is shown as:

$$\begin{bmatrix} 58 & 2 \\ 0 & 60 \end{bmatrix}$$

These results highlight the effectiveness of the composed image modality and the custom-designed Hpt-Net model in improving the detection accuracy of hypertension using BCG signals. The superior performance of Hpt-Net underscores its potential for practical applications in continuous and non-invasive monitoring of hypertension.

# CHAPTER – 4

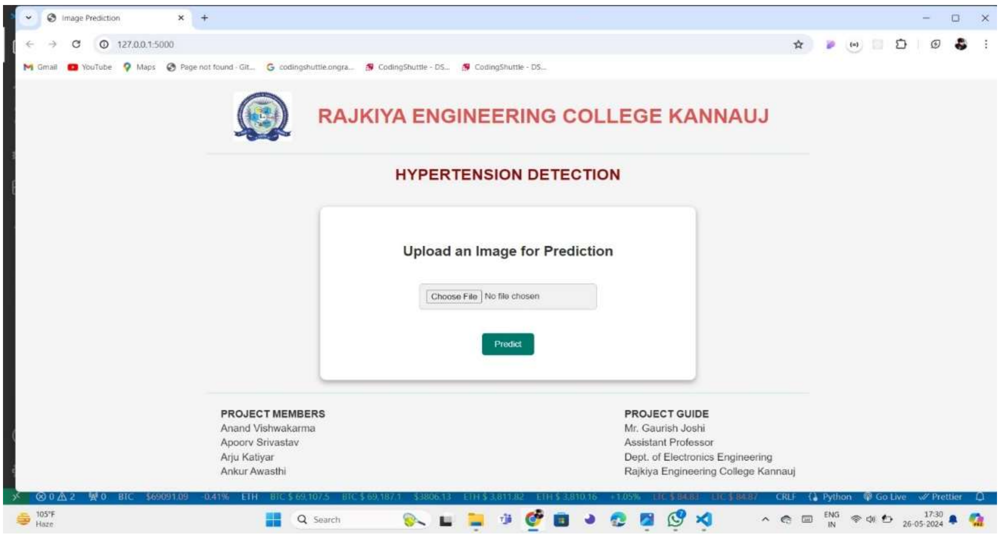
# USER INTERFACE DEVELOPMENT

**4.1 Flask:**
Flask is a lightweight web framwork written python. It is designed to be simple and flexible providing the essentials needed to build web application while allowing developers to choose additional components as needed.

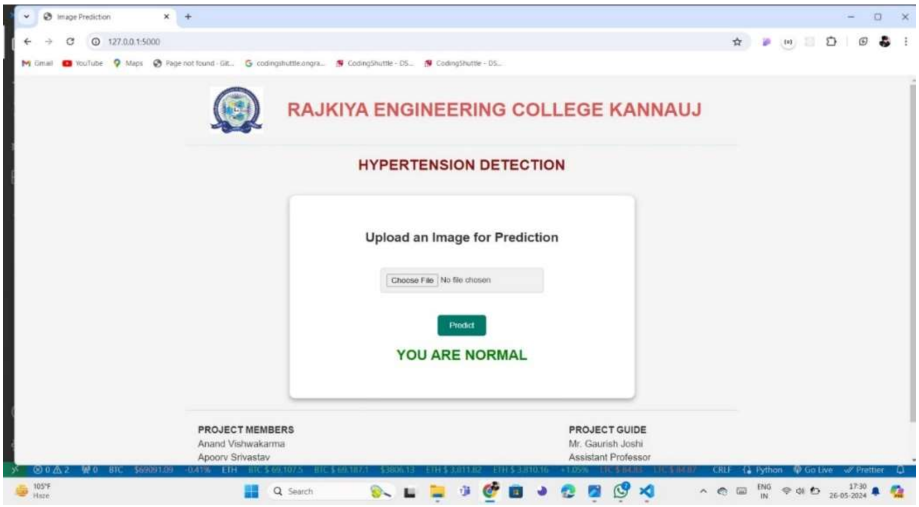
**Key features of flask:**
**1) Minimalistic and Lightweight:** Provides only the essentials, easy to learn and use.
**2) Routing and URL Mapping**: Maps URLs to functions using decorators.
**3) Template Engine (Jinja2):** Supports dynamic HTML generation.
**4) Built-in Development Server**: Include a server with automatic code reloading and a debug.

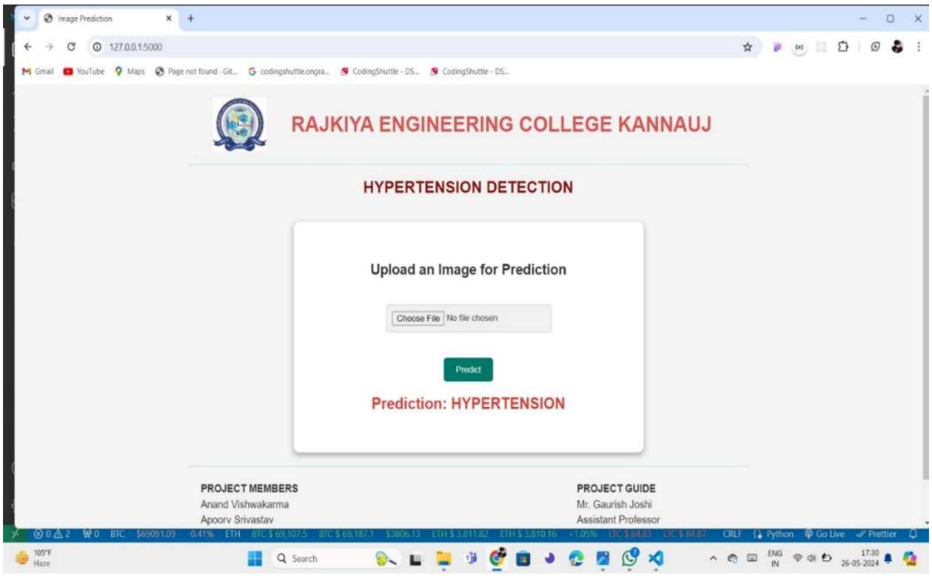
**4.2 User Interface (UI) Design**
For our final year project, we developed a web interface using flask that takes an time series image as inputs and predict hypertension and normal . The user interface (UT) is designed to be intuitive and user-friendly, ensuring ease of use for both technical and non- technical users.

**Ul Components:**
**1) File Uploaders:** The interface includes one file upload components
**2)Time series Image Uploader:** Allows the user to upload a corresponding image file.
**3)Submit Button**: After uploading the images, the user can click the 'Submit' button and predict the hypertension or normal
**4)Display:** The interface displays the hypertension and normal after uploading the images.




**4.3 Steps for using the Web Interface:**
**1. Upload images:** The user uploads an images by clicking on uploader file and selecting appropriate file from their device.
**2. Submit the predict button:** The user click the predict button and frontend call the model after that they predict hypertension or normal.
**3.View Result:** after submit the button user interface displayed the hypertension or normal on the screen.


RAJKIYA ENGINEERING COLLEGE KANNAUJ
HYPERTENSION DETECTION
Upload an Image for Prediction
Choose File No file chosen
Predict
YOU ARE NORMAL
PROJECT MEMBERS
Anand Vishwakarma
Apoorv Srivastav
PROJECT GUIDE
Mr. Gaurish Joshi
Assistant Professor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HYPERTENSION DETECTION
Upload an Image for Prediction
Choose File No file chosen
Predict
Prediction: HYPERTENSION
PROJECT MEMBERS
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# CONCLUSION AND FUTURE WORK

This paper introduces a novel deep neural network for detecting hypertension, named Hpt-Net, which is specifically designed for binary classification of ballistocardiogram (BCG) signal composed image modalities. The model's architecture leverages the complexity of BCG signals to accurately identify the presence of hypertension. The evaluation of the Hpt-Net model is based on several performance metrics, including accuracy, recall, precision, and F1 score. The results indicate that the Hpt-Net model achieves an impressive average accuracy of 98.33%, demonstrating its high efficacy in correctly classifying hypertension cases. In contrast, the widely-used ResNet50 pre-trained model achieves a significantly lower average accuracy of 87.50%, highlighting the superior performance of Hpt-Net in this specific application. Additionally, the paper provides a comparative analysis with the latest existing work in the domain, further illustrating the advantages of the Hpt-Net model in terms of classification accuracy. This comparison underscores the potential of Hpt-Net as a more reliable and effective tool for hypertension detection. The paper also suggests future research directions, emphasizing the exploration of transfer learning to enhance the utility and efficacy of the proposed model. By incorporating transfer learning, Hpt-Net could be trained on new and diverse datasets, improving its robustness and adaptability for time-critical applications in the medical field. This approach could facilitate the development of more generalized and efficient deep learning models for hypertension detection, ultimately contributing to better healthcare outcomes.

- **Develop a wearable device:** Design a wearable device that can comfortably and continuously capture BCG signals for long-term monitoring.
- **Integrate with mobile apps:** Create a mobile application that interfaces with the wearable device to display blood pressure readings, track trends, and potentially offer lifestyle management advice.
- **Remote patient monitoring:** Develop a system for remote patient monitoring using BCG-based blood pressure data, enabling better management for individuals with hypertension.
- **Explore different machine learning models:** Experiment with various machine learning algorithms besides the one you currently use. This might identify models that perform better or provide more interpretable results.
- **Increase data size and diversity:** Include more participants in your study with a wider range of ages, ethnicities, and health conditions. This will improve the generalizability of your model.

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