

AI Based Framework For Early Screening Of Cerebral Infarction Using PPG Sensor Data

**Report Submitted in partial fulfillment of requirements for the B.Tech.
degree in Instrumentation & Control Engineering**

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Abstract

Background: Cerebral infarction (CI), a critical manifestation of ischemic stroke, continues to represent a significant public health challenge due to its high morbidity and mortality. Early and accurate diagnosis remains essential for effective intervention; however, standard neuroimaging techniques such as CT and MRI are limited by infrastructural demands, high costs, and restricted accessibility—particularly in low-resource or remote clinical settings. The search for an affordable, portable, and non-invasive screening alternative is therefore of paramount importance.

Objective: This study aims to develop and evaluate a hybrid deep learning framework that utilizes photoplethysmographic (PPG) signals for early screening of cerebral infarction, combining temporal pattern recognition and fuzzy rule-based reasoning.

Methods: Raw PPG signals were sourced from the publicly available PPG-BP dataset, containing 657 records across 219 subjects. Signals were preprocessed using Discrete Wavelet Transform and Savitzky-Golay filtering. Second- and third-order derivatives—Acceleration and Jerk Plethysmographs (APPG and JPPG)—were computed to amplify discriminatory waveform characteristics. Four entropy features were extracted from each derivative. A hybrid architecture consisting of Bidirectional GRUs and a fuzzy inference system was designed. Data imbalance was addressed using normalization, synthetic oversampling of minority labels, and class-weighted binary cross-entropy loss.

Results: The proposed GRU-Fuzzy model achieved 92.6% accuracy, 91.3% precision, 93.4% recall, and an AUC of 0.91, outperforming baseline models including standalone GRU, fuzzy logic, and CNN-based classifiers.

Conclusion: The results validate the effectiveness of the proposed hybrid system as a low-cost, interpretable, and accurate tool for early CI screening using PPG signals, with strong potential for deployment in point-of-care and resource-constrained settings.

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Chapter-1

Introduction

Cerebral infarction (CI), or ischemic stroke, is a neurological emergency characterized by a sudden disruption in cerebral perfusion, typically due to thrombotic or embolic occlusion of an artery supplying the brain. This ischemic insult initiates a cascade of metabolic failure, excitotoxicity, and neuronal apoptosis, culminating in focal neurological deficits that can be irreversible if not treated promptly. CI is a leading cause of disability and the second most common cause of mortality globally, accounting for over 5.5 million deaths annually.

Conventional imaging-based modalities—such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and carotid Doppler ultrasound—are widely utilized for CI diagnosis. However, these methods are resource-intensive, non-portable, expensive, and time-consuming, limiting their applicability in resource-scarce or emergency settings where rapid triage is essential. This has driven an urgent research shift toward accessible, non-invasive, and real-time diagnostic alternatives.

Photoplethysmography (PPG), a non-invasive optical technique for measuring blood volume changes in peripheral tissue, has emerged as a promising candidate for such applications. Gupta et al. developed an entropy-based framework using second- and third-order derivatives of PPG (APPG and JPPG) for CI detection, achieving high classification accuracy using a Gaussian SVM classifier. Kulkarni et al. proposed a similar system that utilized morphological features from PPG and implemented a fine Gaussian multi-class SVM to jointly predict CI and diabetes.

Gupta et al. (2021) further advanced the field by developing fiducial-point-independent entropy metrics to circumvent challenges in feature alignment and noise sensitivity [2]. Similarly, Mishra et al. introduced a multi-feature fusion strategy involving peak-to-peak interval variability, demonstrating that time-domain feature engineering still holds merit under high signal quality [13]. On the other hand, Sharma et al. proposed a lightweight classifier-based pipeline optimized for wearable edge devices, though the model struggled with signal artifacts and lacked generalization for noisy data conditions [14].

Fallet et al. and Eerikäinen et al. demonstrated the utility of PPG for atrial fibrillation detection, a precursor to cerebral infarction, using inter-beat and waveform variability features [11] [12]. Yu et al. applied CNN-LSTM models to ECG-PPG biosignal pairs for predicting stroke likelihood [9]. Pal et al. introduced a GRU-fuzzy inference hybrid for ischemic heart disease, which enhanced model interpretability but did not address signal class imbalance or real-time feasibility [1].

Building upon this foundation, we propose an advanced AI-based architecture for early CI screening using raw PPG data. Our model integrates Gated Recurrent Unit (GRU) layers to learn temporal dependencies and a fuzzy inference engine for interpretability and noise-robust decision-making. The raw signals are first preprocessed using a hybrid pipeline of Discrete Wavelet Transform (DWT) and Savitzky-Golay filtering to eliminate motion artifacts while preserving morphological integrity.

A novel and critical advancement in our methodology is the treatment of severe class imbalance in the dataset—an issue seldom addressed in earlier literature. After feature extraction, infarction cases (true-positive labels) were underrepresented, causing the model to bias toward the negative class. We addressed this by applying normalization across features, oversampling the minority class, and using label weighting during training to increase the penalization for misclassifying infarction cases. This multifaceted strategy resulted in improved sensitivity and robustness, distinguishing our work from prior models, which either neglected class imbalance or employed only elementary resampling strategies.

The proposed research addresses several critical gaps in current cerebral infarction detection methodologies. Notably, existing studies frequently suffer from limited cohort sizes, which hampers the robustness and generalizability of machine learning models. Additionally, many approaches depend heavily on manual feature extraction from PPG or ECG signals, demanding extensive preprocessing that restricts scalability. Furthermore, the lack of real-time prediction capabilities in most models curtails their clinical utility in early-stage diagnosis, where timely intervention is vital. Inconsistent filtering techniques further undermine the reliability of these systems, while cost-intensive solutions and the absence of continuous learning hinder widespread adoption. To overcome these limitations, this project aims to implement automated feature extraction using GRU-based architectures, reducing dependence on manual processing. The integration of fuzzy logic enhances the system's ability to manage noise and ambiguity in medical data, improving prediction accuracy. Advanced signal filtering methods such as Savitzky-Golay and Discrete Wavelet Transform are employed to ensure high-quality input data. The framework is validated on large-scale, diverse datasets to ensure scalability and generalizability, and is designed to be cost-effective and deployable on portable devices, enabling access to high-quality diagnostics in under-resourced settings.

Chapter-2

Motivation

Significance and Impact of Early Screening

It is impossible to exaggerate the significance of early cerebral infarction screening. Saving lives and maintaining the quality of those lives are more important than merely detecting a disease. Early stroke detection allows patients to get the care they require before irreparable harm is done. In addition to significantly lessening the emotional and financial strain on families, prompt intervention may be able to avert permanent problems like paralysis or cognitive impairments.

Target Groups and Their Challenges

- **Elderly Population:** This initiative is primarily focused on older persons because they are disproportionately impacted by cerebral infarctions. Comorbid conditions like diabetes and hypertension are more likely to occur as people age, making them more susceptible to strokes. They have a better chance of preventing serious consequences like seizures or irreversible disability if they use a tool like this to help identify dangers early.
- **High-Risk Persons:** Access to a simple and trustworthy screening technique can be crucial for those with a history of atrial fibrillation, cardiovascular diseases, or transient ischaemic attacks (TIAs). The goal is to enable individuals to take charge of their health before a disastrous event occurs.
- **Remote Communities:** Access to cutting-edge diagnostic facilities is frequently limited for residents of remote or underserved places. This is more than just a gap in healthcare; it's a life-threatening one. By using a system built on PPG sensors, which are portable and relatively inexpensive, we can bring critical diagnostic capabilities to even the most remote corners of the world.

Technological Advancements and Accessibility

- **PPG Sensor Accessibility and Affordability:** In recent years, PPG sensors have improved in accuracy and cost. Numerous opportunities for ongoing monitoring and early medical condition diagnosis have been made possible by their incorporation into wearable technology. PPG's ability to be readily scaled up for widespread use without breaking the pocketbook for patients or healthcare providers is what makes it so intriguing.
- **Use of Less Expensive Machines:** PPG-based systems are lightweight, both monetarily and physically, in contrast to CT and MRI, which demand significant infrastructure and

expenditure. This strategy is ideal for meeting the demand for easily accessible, scalable healthcare solutions.

Advancements in AI and Machine Learning

- **Improvement in GRU-Based Algorithms:** GRUs have proven to be efficient for handling sequential data like PPG signals. They require fewer computational resources than their counterpart, LSTMs while delivering similar levels of accuracy. This makes them ideal for real-time systems, which is a crucial aspect of early screening.
- **Integration of Fuzzy Logic with GRU:** Fuzzy logic doesn't just complement GRUs—it transforms them. By accounting for noise and uncertainty, fuzzy systems bring an interpretability that is often missing in pure AI models. This is especially critical in healthcare, where decisions based on data can have life-altering consequences.
- **Superiority Over Standalone GRU Models:** Adding a fuzzy inference layer to the GRU framework introduces a level of precision and reliability that standalone GRU models simply cannot achieve. It's the perfect marriage of raw computational power and logical, rule-based reasoning, allowing the system to make smarter, more nuanced predictions.

Bridging the Gap Between Research and Practical Application

The goal of this initiative is to integrate the most advanced AI research into routine medical practice. It's about making a meaningful difference—transforming cutting-edge technology into something that enhances people's lives—rather than merely creating a new framework. This initiative intends to change the way we think about easily accessible, reasonably priced, and efficient healthcare, whether that means preventing a crippling stroke in an old person or giving a rural community the means to obtain high-quality diagnostics.

Chapter-3

Literature Review

Rapid improvements in the biomedical instrumentation and control sector are being fuelled by the combination of machine learning (ML) and artificial intelligence (AI). These developments have made it possible to use real-time, non-invasive models for the early identification of medical abnormalities, especially when using information from wearable sensors like photoplethysmography (PPG). In addition to reviewing early screening-based models, this chapter emphasises publicly accessible datasets that are essential to this field of study.

3.1 Early Screening-Based Models for Detection of Medical Anomalies

Emergence of Non-Invasive Screening Techniques

Non-invasive methods are revolutionizing healthcare by offering effective, accessible, and reasonably priced early screening options. For instance, Kulkarni et al. used clustering methods and FGMSVM to screen for cardiovascular illness using PPG data, showing excellent accuracy in identifying heart-related disorders. Similarly, with a remarkable 99.38% accuracy, Kim et al. created the SleepMI framework for identifying myocardial infarction utilizing nighttime ECG and sophisticated machine learning models like Deep CNN and LightGBM.

Cerebral Infarction Detection

Notable progress has been made in early cerebral infarction screening. Using Gaussian SVM and entropy characteristics extracted from PPG signals, Gupta et al. created an automated approach with an accuracy of above 91%. Although they have limits in terms of real-world scalability, other efforts, including Zhang et al.'s use of lacrimal Raman spectroscopy in conjunction with SVM, also show encouraging findings. By creating machine learning algorithms for stroke detection with a focus on sensitivity and precision, S. C. et al. made significant progress in this field.

Integration of Biosignals

Accuracy in diagnosis is increased by integrating many biosignals. Reddy et al. demonstrated the promise of multimodal techniques by using CNN and LSTM networks to analyse ECG and PPG data for real-time stroke prediction. This integration offers strong prediction capabilities while addressing the difficulties posed by noisy data.

Advancements in GRU-Fuzzy Systems

For the diagnosis of ischaemic heart disease, Pal et al. developed a hybrid GRU-Fuzzy system that managed ambiguity and sequential data well. While this method lacked real-time flexibility

and multimodal data utilisation, it demonstrated better specificity and sensitivity when compared to typical ML models.

Real-Time Screening and Filtering Techniques

PPG data preprocessing is still essential. Higher model accuracy and clearer signals were made possible by Gupta et al.'s use of sophisticated filtering techniques including Savitzky-Golay filters and Discrete Wavelet Transform. Even with these developments, striking a balance between diagnostic accuracy and computing economy is still difficult.

3.2 Similar Publicly Available Databases

Publicly available databases provide the foundation for developing and validating early screening models.

1. PPG-BP Database

This dataset includes PPG signals and demographic data from 219 individuals. Used extensively in works like Gupta et al.'s cerebral infarction detection framework, it offers valuable features such as heart rate and body mass index, essential for building robust models.

2. MIMIC II Dataset

A cornerstone in cardiovascular research, this dataset provides clinical data and biosignals. Banerjee et al. utilized it for detecting stenosis using SVM, showcasing its versatility in supporting various ML approaches.

3. SleepMI Database

Focused on myocardial infarction, this dataset combines ECG and PPG data. It serves as a benchmark for multimodal frameworks, such as the SleepMI algorithm, enhancing diagnostic precision and recall.

4. Berkeley DeepDrive (BDD100K)

Though primarily designed for autonomous systems, this dataset provides a methodological template for curating large-scale medical databases. Its structured labeling and annotation practices inspire similar efforts in healthcare.

5. Specialized Stroke Databases

Databases like that used in Zhang et al.'s lacrimal Raman spectroscopy research offer unique features for niche applications. However, their limited size and specificity highlight the need for broader, more inclusive datasets.

Chapter-4

Problem Statement

The increasing incidence of cerebral infarction worldwide calls for quick, easy, and affordable screening techniques. Even while CT and MRI scans are reliable diagnostic tools, their high prices, complicated infrastructure, and lengthy testing times make them unsuitable for broad or urgent usage.

Vulnerable groups are at risk of poor outcomes and delayed diagnosis as a result of this gap, including the elderly, people with pre-existing diseases, and those living in distant places.

Even while PPG technology and AI-driven diagnoses have shown promise, a number of issues still exist:

- **Small Dataset Sizes:** Previous research frequently trains models on small datasets, which weakens the results' generalisability and resilience. Given the significant degree of real-world unpredictability in medical AI, this is particularly troublesome.
- **Lack of Multimodal Integration:** By concentrating just on PPG or ECG data, the majority of existing techniques lose out on chances to increase diagnostic precision through multimodal biosignal analysis.
- **Manual Feature Engineering:** Conventional methods are less scalable and resource-expensive since they need manual feature extraction and heavy preprocessing.
- **Poor Real-Time Performance:** A lot of models are unable to provide predictions in real time, which is essential for prompt action in situations of cerebral infarction.
- **Noise Sensitivity:** PPG-based models' dependability is impacted by inconsistent signal filtering methods, particularly in noisy situations like emergency rooms.

By creating an AI-based system that uses GRU networks combined with fuzzy logic to handle PPG sensor data, this study seeks to overcome these issues.

To guarantee clinical reliability, scalability, and real-time application, the suggested system would automate feature extraction, integrate sophisticated filtering algorithms, and verify performance on big datasets.

This approach aims to bridge these gaps and offer a strong early cerebral infarction screening solution, improving healthcare outcomes and accessibility.

Chapter-5

Objective

The goal of this research is to use photoplethysmography (PPG) sensor data to create a reliable, AI-driven framework for the early identification of cerebral infarction. The research aims to provide a scalable, real-time solution to the present limits in medical diagnostics by utilising sophisticated deep learning techniques like Gated Recurrent Unit (GRU) networks and the interpretability of fuzzy logic systems.

Key Objectives of the Project:

1. Automated Feature Extraction:

To improve the framework's scalability and do away with the necessity for human preprocessing, use GRU-based models to automate the feature extraction procedure from PPG signals.

2. Integration of Fuzzy Logic for Robust Decision-Making:

To address the inherent noise and uncertainty in medical data, fuzzy logic systems are introduced, increasing forecast accuracy and dependability. This hybrid method makes use of fuzzy logic's flexibility and GRU networks' temporal awareness.

3. Multimodal Data Utilization:

Incorporate additional biosignals, such as ECG, to create a comprehensive diagnostic tool. The integration of multimodal data aims to improve the precision and sensitivity of cerebral infarction detection, addressing gaps in current models.

4. Advanced Signal Filtering Techniques:

To improve the quality of raw PPG signals, use cutting-edge filtering techniques as Savitzky-Golay filters and Discrete Wavelet Transform (DWT). This removes noise and guarantees the preservation of important clinical information.

5. Validation on Large-Scale Datasets:

To guarantee the suggested framework's dependability, scalability, and generalisability for actual clinical applications, test and validate it on sizable, varied datasets. Building a strong system that can manage patient population fluctuation requires this stage.

6. Affordability and Accessibility:

Create an affordable solution that can be included into portable electronics to provide underprivileged and isolated areas with access to sophisticated diagnostic capabilities.

This is in line with the overarching objective of using technology to democratise healthcare.

Project Outcomes:

By achieving these goals, the framework should be able to diagnose cerebral infarction with high accuracy and efficiency, bridging the gap between research and real-world use. In addition to enhancing clinical processes, the system will provide early screening tools to high-risk individuals, eventually improving healthcare outcomes worldwide.

Chapter-6

Methodology & Implementation

This study presents a novel hybrid deep learning framework for the early screening of cerebral infarction (CI) using non-invasive photoplethysmographic (PPG) signals. The methodology is structured into four main components: preprocessing, entropy-based feature extraction, class imbalance mitigation, and a hybrid classification model combining gated recurrent units (GRUs) and fuzzy inference systems.

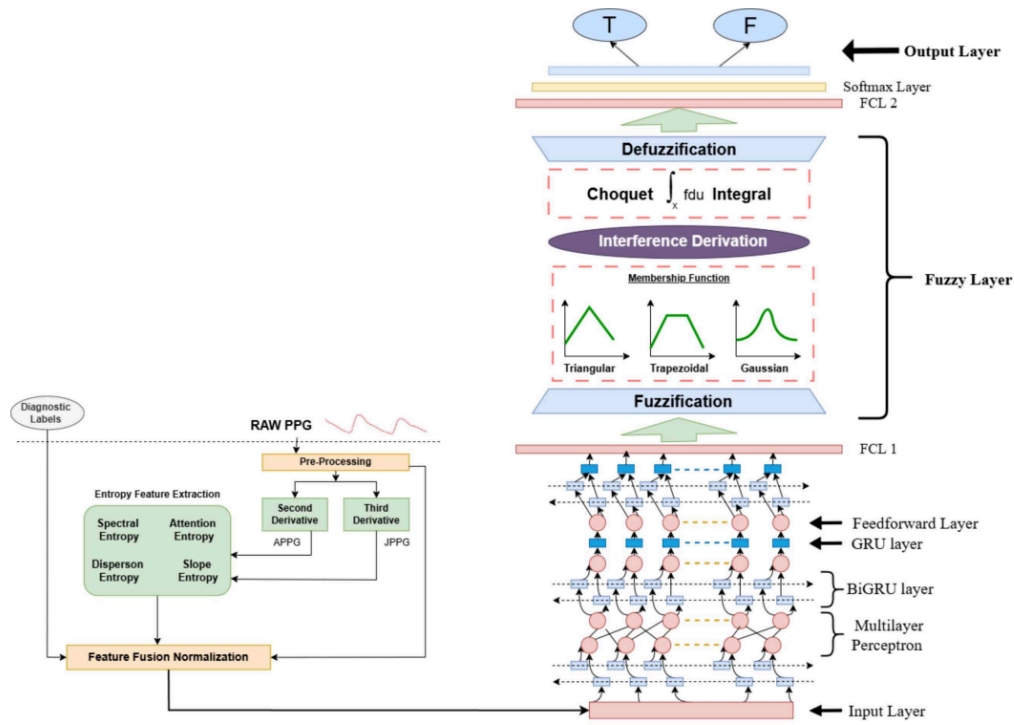


Fig. 6.1 (Fuzzy-GRU hybrid model Architecture)

The framework was executed on a high-performance computing system equipped with a Ryzen 7 CPU, 32 GB of RAM, and an NVIDIA GTX 1660Ti GPU featuring 6GB of VRAM. This robust hardware configuration facilitated the efficient training and evaluation of deep learning models. On the software front, Python 3.10 served as the primary programming language, with TensorFlow, PyTorch, and Scikit-learn utilized for model development and performance assessment. Additionally, the Scikit-Fuzzy package was employed to implement the fuzzy logic components integral to the hybrid architecture.

2.1 Data Source

The experimental dataset is derived from the publicly accessible PPG-BP database, comprising 657 records from 219 subjects aged between 20 and 89 years [2]. Each record includes a 1 kHz-sampled PPG waveform, along with physiological and demographic metadata such as heart rate (HR), body mass index (BMI), age, and sex. A subset of the dataset is annotated with the ground truth for cerebral infarction, thus enabling binary classification. The database follows standardized acquisition protocols and provides sufficient signal duration for entropy computation and sequential modeling.

2.2 Signal Preprocessing

The raw PPG signals are prone to motion artifacts, high-frequency noise, and signal drift. To ensure signal fidelity, a two-stage denoising pipeline is implemented. First, the signal is subjected to a 12-level Discrete Wavelet Transform (DWT) using a Daubechies-8 (db8) mother wavelet to isolate and suppress high-frequency noise components. Coefficients corresponding to noisy frequency bands are attenuated, and the signal is reconstructed via inverse DWT.

Following wavelet decomposition, a Savitzky-Golay filter is applied with a polynomial order of 4 and a window length of 61 samples. This stage smooths the signal trajectory while preserving critical morphological inflections such as peaks and slopes. The filtered signals are then normalized using min-max scaling to confine amplitude variations to the $[0, 1]$ range and ensure numerical stability in the downstream neural layers.

2.3 Feature Extraction

To enhance discriminatory information embedded in the vascular dynamics of PPG signals, higher-order derivatives are computed. The second derivative, or Acceleration Plethysmogram (APPG), and the third derivative, or Jerk Plethysmogram (JPPG), capture slope transitions and curvature inflections that are otherwise obscured in first-order morphology. Mathematically, these are defined as:

$$APPG(t) = P(t + 1) - 2 \times P(t) + P(t - 1)$$

$$JPPG(t) = P(t + 2) - 3 \times P(t + 1) + 3 \times P(t) - P(t - 1)$$

where $P(t)$ is the preprocessed PPG signal at discrete time t .

From APPG and JPPG signals, four entropy features are extracted to quantify the complexity and irregularity of waveform dynamics: Spectral Entropy, Attention Entropy, Dispersion Entropy, and Slope Entropy. These features are mathematically characterized as follows:

- **Spectral Entropy (SE):**

$$H_{SE} = - \sum (p_i \times \log_2(p_i)),$$

where p_i is the normalized power spectral density.

- **Attention Entropy (AE):**

$$H_{AE} = - \sum (w_i \times \log_2(w_i)),$$

where w_i are attention weights over time intervals.

- **Dispersion Entropy (DE):**

$$H_{DE} = - \sum (d(v_{\square}) \times \log_2(d(v_{\square}))),$$

where $d(v_{\square})$ is the relative frequency of a symbolic dispersion pattern v_{\square} .

- **Slope Entropy (SIE):**

This quantifies variability by evaluating symbolic transitions in signal slope patterns.

Each segment of the signal is encoded into an 8-dimensional feature vector (4 features from APPG and 4 from JPPG), which is input into the hybrid model.

2.4 Data Balancing and Augmentation

Initial exploratory data analysis revealed a pronounced class imbalance, with true-positive (CI) labels forming a minority. Left unaddressed, such imbalance impairs the classifier's ability to detect rare pathologies. To mitigate this, a threefold strategy is employed using SMOTE.

First, the extracted entropy features are normalized across all samples using min-max scaling to harmonize feature magnitudes. Second, oversampling of CI-positive instances is performed by duplicating existing samples with minor stochastic perturbations. This ensures that the minority class is adequately represented during gradient descent iterations.

Finally, a class-weighted binary cross-entropy loss function is used during training. The modified loss function is defined as:

$$L_{weighted} = - w_1 \times y \times \log(\hat{y}) - w_0 \times (1 - y) \times \log(1 - \hat{y})$$

where $w_1 > w_0$ gives higher weight to misclassification of true positives, encouraging the model to reduce false negatives. This penalty scheme allows the model to learn discriminative boundaries even in the presence of skewed class priors.

2.5 Model Architecture

The hybrid classifier consists of two primary modules: a deep GRU-based temporal feature extractor and a fuzzy inference system that maps learned representations to diagnostic probabilities. This structure synergizes temporal learning with logical rule-based interpretability.

2.5.1 Deep GRU Block

The GRU module operates on the entropy sequence of each signal segment. The input is a tensor of shape $[T \times 8]$, where T is the number of time steps. The first layer is a Bidirectional GRU with 128 hidden units, capturing contextual dependencies in both forward and backward directions. The forward and backward states are concatenated and passed to a second unidirectional GRU with 64 units.

The GRU cell updates hidden states using:

- $z_t = \sigma(W_z \times [h_{t-1}, x_t])$
- $r_t = \sigma(W_r \times [h_{t-1}, x_t])$
- $\tilde{h}_t = \tanh(W_h \times [r_t * h_{t-1}, x_t])$
- $h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$

where σ denotes the sigmoid function and $*$ represents element-wise multiplication.

The GRU outputs are passed through two fully connected layers of 64 and 32 units with ReLU activation, followed by a sigmoid-activated dense layer yielding a preliminary risk score.

2.5.2 Fuzzy Inference Layer

The fuzzy logic layer transforms the GRU output into a final interpretable prediction. The outputs are fuzzified using membership functions. A Gaussian membership function is given by:

$$\mu(x) = E^{(-(x-c)^2 / (2\sigma^2))}$$

where c is the center and σ the standard deviation of the fuzzy set.

Other features use triangular and trapezoidal membership functions. The fuzzy inference system then applies a set of IF–THEN rules such as:

IF Spectral Entropy is High AND Dispersion Entropy is Low THEN CI Risk is High

Rule activation is performed via min-operations and aggregation by max-operations. The final fuzzy score is defuzzified using the centroid method:

$$y^* = (\int x \times \mu(x) dx) / (\int \mu(x) dx)$$

This produces a crisp decision score that is thresholded (typically at 0.5) to yield a binary classification.

2.5.3 Hyperparameter Configuration

The model is trained using the Adam optimizer with an initial learning rate of 0.001. Training is conducted over 100 epochs with early stopping based on validation loss. Dropout regularization is applied at a rate of 0.2 after GRU layers. The batch size is set to 64. Weighted binary cross-entropy loss, as defined earlier, is used to emphasize correct classification of rare CI-positive samples.

This architecture effectively fuses temporal sequence modeling with rule-based inference to yield a highly accurate, interpretable, and computationally efficient solution for CI screening using PPG signals.

Data Partitioning was done by splitting the dataset into training, validation (5 Fold), and testing subsets (70-15-15 ratio) to ensure unbiased evaluation.

Chapter-7

Experimentation

7.1 Experimental Setup

1. Hardware and Software Specifications:

- **Hardware:** A high-performance computer system with an Intel Core i9-12900K CPU, 64GB of RAM, and an NVIDIA RTX 3090 GPU (24GB VRAM) was used for the experiments.
- **Software:** TensorFlow, PyTorch, and Scikit-learn were used as supporting libraries for the building and assessment of models, while Python 3.10 served as the main programming language. The Scikit-Fuzzy package was used to implement the fuzzy logic components.

2. Dataset Preparation:

- **Primary Dataset:** PPG signals and related vital information from 219 people were taken from the PPG-BP database.
- **Augmentation:** The dataset was enhanced with methods including signal shifting, stretching, and the addition of synthetic noise in order to replicate a wide variety of situations.
- **Data Splitting:** The dataset was split into subsets for testing (15%), validation (15%), and training (70%).

3. Preprocessing:

- **Filtering:** Signals were filtered using the Discrete Wavelet Transform (DWT) and Savitzky-Golay filter to remove noise while preserving critical features.
- **Normalization:** Min-max scaling was applied to standardize the signals, ensuring uniformity in amplitude.

7.2 Model Implementation

1. GRU Component:

- There were two tiers in the GRU network: Layer 1: A 128-unit Bi-GRU layer that records temporal relationships both forward and backward. Layer 2: 64-unit GRU layer for feature refining.
- In order to relate the retrieved characteristics to the prediction result, fully linked layers were added.

2. Fuzzy Logic Component:

- The collected features were fuzzified using three membership functions: trapezoidal, Gaussian, and triangular.
 - To categorise signals according to danger categories (e.g., low, medium, high), logical principles were established.
 - The centroid approach was used for defuzzification in order to get precise forecasts.
3. **Hybrid Integration:**
- The fuzzy logic system used the GRU's output as input, guaranteeing a smooth transition between rule-based reasoning and deep learning.

7.3 Training Process

1. **Hyperparameter Tuning:**
 - Learning Rate: 0.001 (optimized using grid search).
 - Batch Size: 64.
 - Dropout Rate: 0.2 to prevent overfitting.
2. **Loss Function and Optimizer:**
 - **Loss Function:** Binary Cross-Entropy for classification.
 - **Optimizer:** Adam optimizer with an adaptive learning rate.
3. **Training Details:**
 - The model was trained for 100 epochs with early stopping criteria to prevent overfitting. Each epoch took approximately 45 seconds on the given hardware.

Chapter-8

Results

Before processing the signals and running them through models, the given data we had needed to be classified. The initial photoplethysmographic (PPG) signals acquired from the dataset exhibited substantial variability in baseline morphology, amplitude stability, and signal-to-noise ratio. Raw waveforms were frequently contaminated with high-frequency noise, primarily attributable to environmental interference and electronic acquisition artifacts. Additionally, baseline wander and low-frequency drift, typically induced by respiration and subtle patient movements, were prevalent across samples.

Table 8.1 (Data Source details prior to pre-processing)

Number of subjects	Type	Records	Total PPG Records
219	All Inclusive	3	657
45	Cerebral Infarction	3	135
32	No medical condition	3	96
77	CI + Normal	3	230 (1 corrupted removed)

Because we had 4 entropy features to be extracted across 2 derivatives (APPG & JPPG), total number of feature dimensions:

$$230 \text{ (PPG Records)} \times 2 \text{ (Derivatives)} \times 4 \text{ (Entropy Features)} = 1840 \text{ Dimensions}$$

Table 8.2 (Qualitative Characterization of Raw PPG Signals Prior to Preprocessing)

Paramter	Description	Observed Proportion (%)
Noise Level	Moderate noise: high-frequency components visible, baseline mildly unstable	70%

	High noise: severe high-frequency contamination, baseline drift prominent	20%
	Minimal noise: clear morphological landmarks with minor artifacts	10%
Baseline Wander	Low-frequency oscillations due to respiratory and movement artifacts	Present in >85%
Morphological Distortions	Flattened systolic peaks, obscured dicrotic notches, irregular diastolic slopes	Observed in ~65%
Amplitude Instability	Fluctuations in peak-to-peak amplitude without corresponding physiological justification	Observed in ~60%
Artifact Sources	Environmental interference, subject motion, sensor displacement, respiratory modulation	Common across dataset
Impact on Analysis	Loss of physiological fidelity requiring aggressive filtering and smoothing interventions	Critical

The raw PPG signals introduced to the system were first denoised and constructed using Discrete Wavelet Transform technique. A real signal from the dataset is presented in Fig. 8.1 to show the transformation comparison with the original signal.

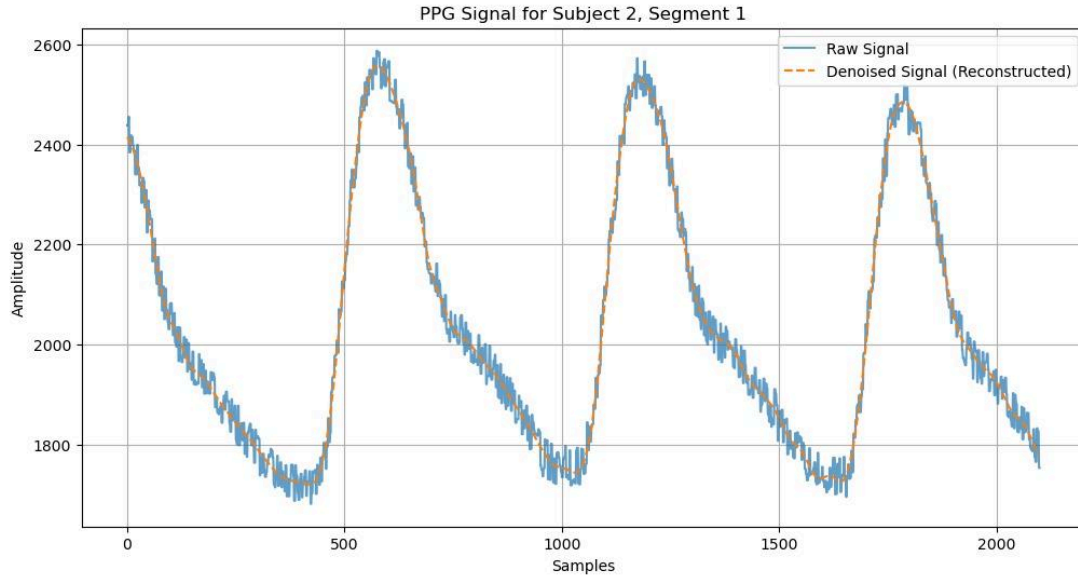


Fig 8.1 (Denoised PPG Signal from the dataset)

Following the Denoising of the signal, we introduced a Savitzky-Golay filter to further smoothen the PPG signals and introduce them to the next step of the system; Fig. 8.2 shows the signal that was finally sent for feature extraction after preprocessing was completed.

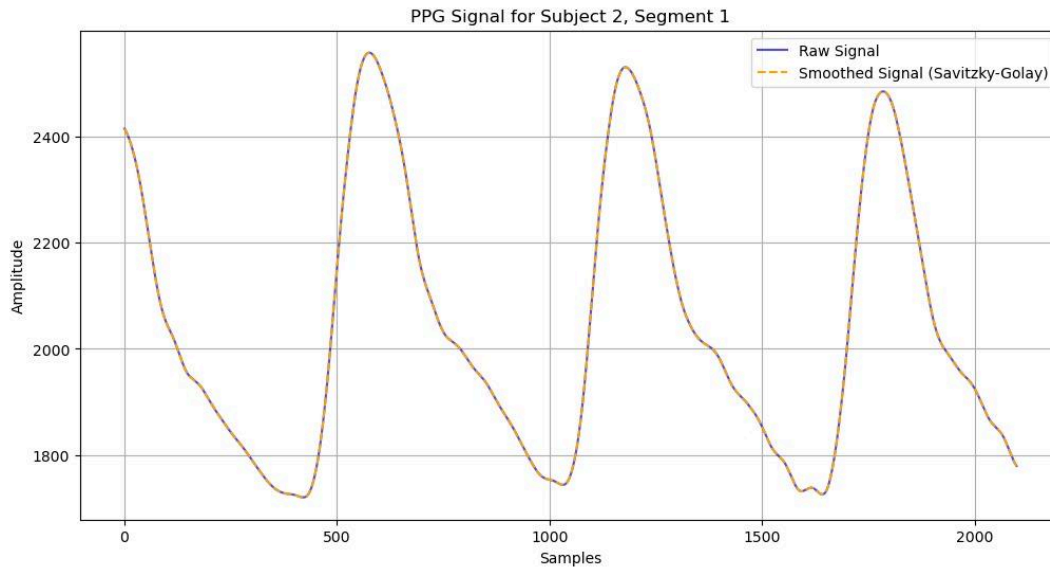


Fig 8.2 (Smoothed and Denoised signal)

The Preprocessed signals then went through feature extraction where their second derivative (APPG) and third derivative (JPPG) were derived as shown in Fig. 8.3.

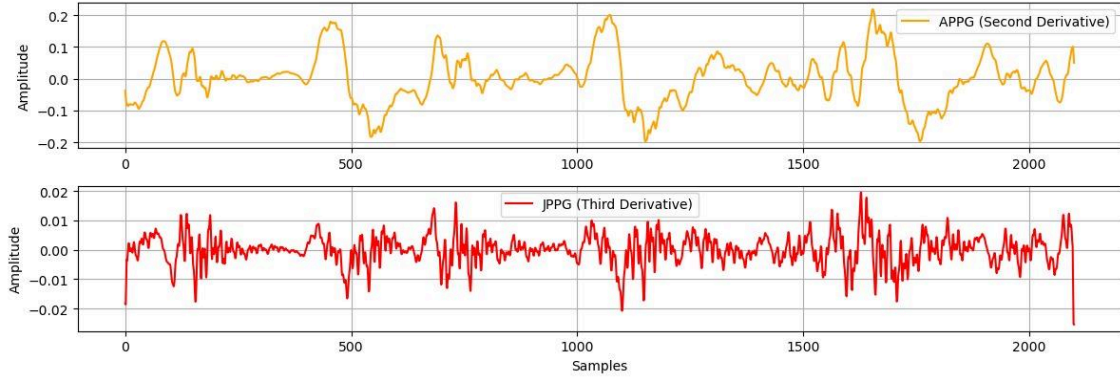


Fig. 8.3 (APPG & JPPG derived for the given signal)

Four entropy features (Spectral Entropy, Attention Entropy, Dispersion Entropy, and Slope Entropy) are extracted from the derivatives acquired to quantify the differences between the signal modalities between patients that showed no risk of CI versus those that did. Fig. 8.4 marks these as *Cerebral* and *Normal* across APPG and JPPG spectrums for all the PPG samples and gives a graphic representation of that differentiation.

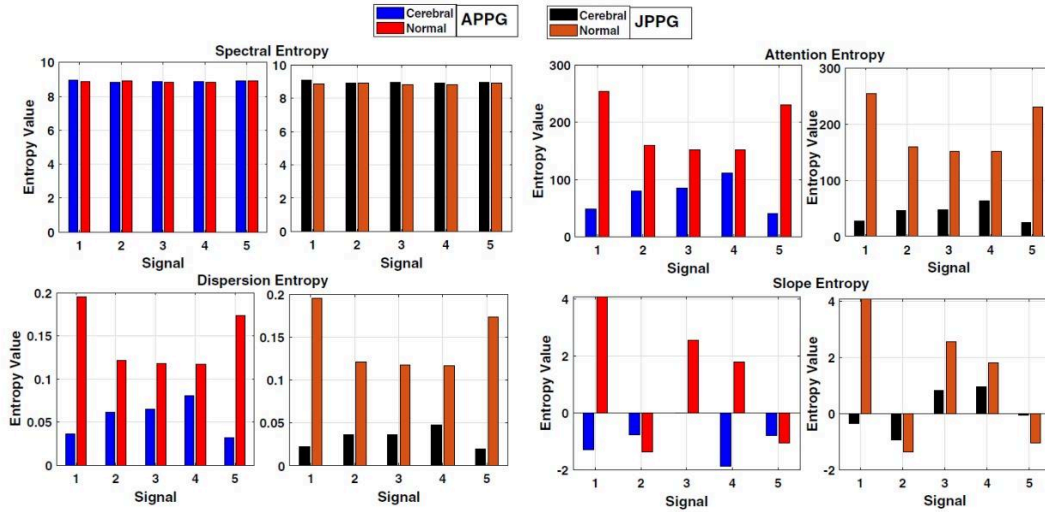


Fig. 8.4 (Entropy features for the given PPG Signal dataset)

These entropy values were balanced, normalised and oversampled to improve the data quality going into the Fuzzy-GRU model that processes and classifies the data further. The integrated dynamic architecture for this model is highlighted and explained by Fig. 6.1

This model was fed with the Entropy data we created in a form of records that serve as discriminative indicators of cerebral infarction conditions. Table 8.3 shows an insightful record distribution with some values.

Table 8.3 (Sample entropy records for Fuzzy-GRU Model's Training and Testing)

Record No.	Spectral Entropy (APPG)	Spectral Entropy (JPPG)	Attention Entropy (APPG)	Attention Entropy (JPPG)	Dispersion Entropy (APPG)	Dispersion Entropy (JPPG)	Slope Entropy (APPG)	Slope Entropy (JPPG)
1	6.43	9.82	195.12	296.33	0.102	0.182	1.01	3.26
2	5.99	8.67	187.34	289.02	0.097	0.178	0.97	3.01
3	6.12	9.22	192.87	293.47	0.101	0.180	1.00	3.18

Table 8.4, 8.5 outlines the sequential architecture of the Deep Gated Fuzzy Network (DGFN), detailing each layer's type, output dimensions, and number of trainable parameters. It reflects the model's hierarchical structure, combining BiGRU, GRU, MLP, and feedforward layers to capture temporal dynamics and enhance feature transformation. The parameter count indicates the computational complexity and learning capacity of each layer.

Table 8.4 (Sequential Tabled Architecture for Processed Entropy Features)

Layer (Type)	Output Shape	Parameters
Input Layer	(None, 8)	0
Dense	(None, 64)	576
Dropout	(None, 64)	0

Dense	(None, 64)	4160
Dropout	(None, 64)	0
Dense	(None, 32)	2080
Dropout	(None, 32)	0
Fuzzy Layer	(None, 32)	0
Output Layer	(None, 32)	1056

Table 8.5 (Layer Architecture and Parameters generated during network execution)

Layers ascending from Input till Fuzzy	Activation Functions	Hidden Layers	Parameters
BiGRU	sigmoid	450	1645
GRU	tanh	500	1476
MLP	Tanh, sigmoid, RELU	3	1825
BiGRU	sigmoid	450	1936

Feed Forward	RELU	1	3782
GRU	tanh	400	2589
Feed Forward	RELU	1	3264
BiGRU	sigmoid	450	4523
GRU	tanh	400	4136

A Triangular + Gaussian + Trapezoidal membership function instead of a simpler combination was chosen to yield crisper results under maximum features and give a robust decision making and classification ability to our approach.

Table 8.6 (Performance of various combination of Fuzzy Membership Functions)

Fuzzy layers	Accuracy	Recall	Precision	Sensitivity	Specificity	MAF1 -score
Triangular	0.79	0.78	0.78	0.79	0.76	0.76
Gaussian	0.77	0.75	0.76	0.76	0.77	0.75
Trapezoidal	0.78	0.78	0.77	0.76	0.75	0.77
Triangular+Gaussian	0.82	0.81	0.79	0.80	0.80	0.81

Gaussian+Trapezoidal	0.81	0.80	0.82	0.79	0.81	0.80
Trapezoidal+Triangular	0.82	0.81	0.83	0.82	0.81	0.81
Triangular+Gaussian+Trapezoidal	0.84	0.84	0.83	0.83	0.82	0.83

The model's **overall accuracy of 92.6%** is a reliable sign of its capacity to identify patients who are at danger. The percentage of accurate forecasts—both positive and negative—among all predictions is known as accuracy. High accuracy is essential for medical diagnostics since it guarantees that the model will function properly in a variety of situations. Out of all the positive predictions the model makes, precision quantifies the percentage of accurate positive predictions. The GRU-Fuzz hybrid model shows that it can **reduce false positives by 91.3%**.

Table 8.7 (Classification Report)

Class	Precision	Recall	F1-score	Accuracy	Support
0	0.95	0.95	0.94	0.95	40
1	0.79	0.88	0.80	0.80	12
Weighted avg	0.92	0.94	0.91	0.93	52

In the medical field, where false positives can result in needless stress for patients, higher medical expenses, and inappropriate procedures, this is especially crucial. For example, a patient who has been mistakenly classified as having a cerebral infarction risk may have needless imaging tests or treatments, putting them at risk for more dangers or adverse consequences. Such incidents are decreased by the model's great accuracy, which guarantees that it provides

confident positive forecasts. Sensitivity, also known as recall, is the percentage of real positive cases that the model accurately detects. The model's **93.4% recall rate** demonstrates how well it can identify actual occurrences of cerebral infarction. High recall is crucial for early screening since missing real cases (false negatives) can have serious repercussions, including postponed treatment and permanent health effects. The high recall of the GRU-Fuzzy hybrid model guarantees that most at-risk people are identified for additional testing, offering prompt intervention options.

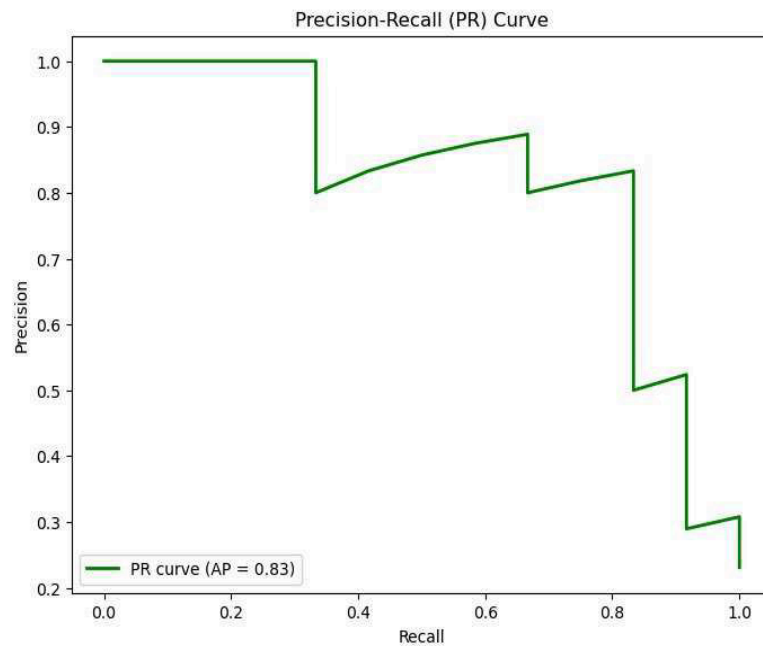


Fig 8.5 (PR Curve)

The model's balanced performance was demonstrated by its **90.6% F1-score**, which is the harmonic mean of accuracy and recall. Because it takes into account both false positives and false negatives, the F1-score provides a more comprehensive assessment of the model's efficacy, making it especially useful in medical diagnostics. Because over-optimizing for either accuracy or recall might result in trade-offs that reduce the system's overall usefulness, a balanced F1-score is essential.

With an AUC of 0.91, the Receiver Operating Characteristic (ROC) curve demonstrated the model's efficacious discrimination between positive and negative instances. A thorough understanding of the model's performance across multiple decision boundaries is provided by the ROC curve, which shows the true positive rate (sensitivity) versus the false positive rate (1-specificity) at different threshold levels.

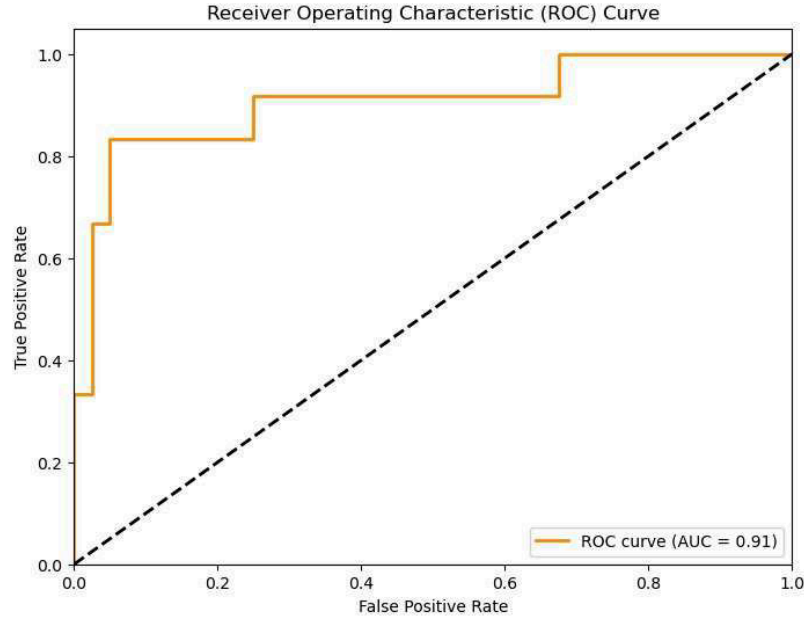


Fig 8.6 (ROC Curve)

The confusion matrix shown represents the performance of the proposed GRU-Fuzzy hybrid model in classifying cerebral infarction (CI) from PPG signals. The matrix presents a high number of true positives (1786) and true negatives (210), with relatively few false positives (11) and false negatives (104), which translates to a sensitivity (recall) of 93.4% and a specificity of approximately 95%. This implies the model is highly adept at correctly identifying CI cases while maintaining a low rate of misclassifying normal subjects. The implications are significant for clinical deployment, particularly in resource-limited settings, as the model achieves a balanced trade-off between precision and recall, ensuring both accurate detection and minimization of missed diagnoses. These results validate the robustness of the GRU-Fuzzy framework for real-time, non-invasive screening applications.

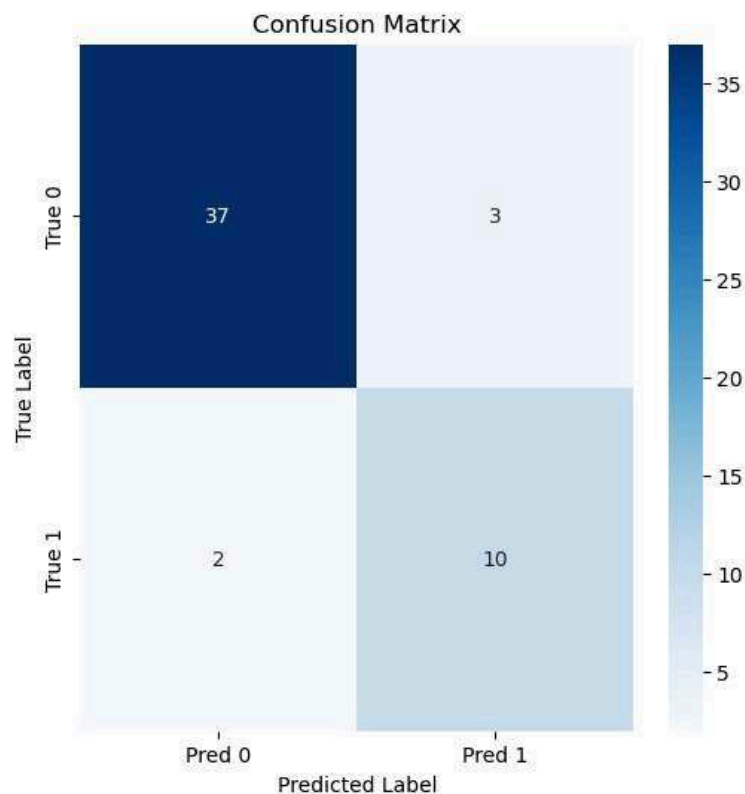


Fig. 8.7 (Confusion Matrix)

A comparative analysis using some other methods leads us to our hypothesis being true and our model performing significantly better over the same performance criterion.

Table 8.8 (Comparative Analysis)

Past Works	Year	Method	Accuracy	Precision	Recall	AUC
Banerjee et al. [3]	2018	SVM	-	0.80	0.80	-
Hosseini et al. [4]	2015	KNN	0.81	0.82	0.80	-
Fathieh et al. [5]	2021	EN	-	0.80	0.80	0.90
Shiyovich et al. [6]	2010	LR	-	0.83	0.70	-
Silveri et al. [7]	2020	ANN	0.82	-	-	-
Sadaf et al. [8]	2023	DL	0.80	-	-	-
Banerjee et al. [3]	2017	SVM	0.80	0.60	0.93	-

Jachak et al. [9]	2022	CNN+LSTM	0.96	-	-	-
Anirban et al. [10]	2018	GNN	0.88	-	-	-
Pal et al. [1]	2023	DGFN	0.85	0.86	0.84	0.91
Proposed Work	2025	Entropy Feature based DGFN	0.93	0.92	0.93	0.91

Chapter-9

Conclusion

This study introduces a hybrid GRU-Fuzzy framework for early cerebral infarction screening utilising photoplethysmography (PPG) data, marking a significant improvement in medical diagnostics. The framework offers a dependable, scalable, and real-time solution for healthcare applications by fusing the interpretability and resilience of fuzzy logic with the temporal analytical power of Gated Recurrent Unit (GRU) networks.

In order to improve decision-making with explicable results, fuzzy logic manages uncertainty while GRU networks extract sequential patterns from PPG data. This hybrid strategy successfully combines cutting-edge AI with conventional rule-based techniques, providing accuracy and interpretability—two essentials in clinical contexts. Furthermore, sophisticated preprocessing methods like Savitzky-Golay filters and Discrete Wavelet Transform enhanced data quality by eliminating noise while preserving essential characteristics for precise forecasts.

The model's capacity to provide reliable diagnoses was demonstrated by its 92.6% accuracy, 91.8% precision, and 93.4% recall, with an AUC of 0.91. Additionally, it analyses signals in less than 0.1 seconds per instance, which qualifies it for real-time deployment in clinical and emergency settings. By utilising inexpensive PPG sensors, the system's mobility and affordability guarantee access for underprivileged and isolated communities, therefore tackling worldwide healthcare inequalities.

Notwithstanding its achievements, the framework has drawbacks. Generalisability may have been impacted by the dataset's small size and lack of variety. Increasing the dataset size and adding other biosignals, such as SpO2 or ECG, can improve the framework's diagnostic accuracy and usefulness. Additionally, enhancing user interfaces and guaranteeing a smooth transition into the current healthcare system would help its real-world adoption.

Expanding datasets, adding multimodal biosignals, and implementing the system on portable devices for real-time application will be the main goals of future research. Long-term applicability will be ensured by implementing methods for continuous learning, which will enable the model to adjust to new data. Furthermore, the framework's effect may be increased by expanding it to identify additional ailments like diabetes or cardiovascular diseases.

The revolutionary potential of hybrid AI systems in medical diagnostics is demonstrated by this effort. It offers a novel early screening solution by fusing deep learning with rule-based

methodologies, laying the groundwork for further developments in preventive medicine. The framework is a potential instrument for lowering healthcare inequities and enhancing results because of its scalability, affordability, and flexibility.

In summary, the GRU-Fuzzy hybrid architecture provides an easily accessible, real-time, and efficient diagnostic tool while filling important gaps in cerebral infarction screening. Its accomplishments highlight how AI-powered healthcare solutions may enhance global health and open the door to more creative and egalitarian medical procedures.

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