EMERGENCY EVENT CLASSIFICATION VIA HYBRID DEEP LEARNING ON SMARTPHONE INERTIAL SENSOR DATA

A Project Report submitted in partial fulfillment of the requirements for the

award of the Degree of

Bachelor of Technology
in
Computer Science and Engineering

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CERTIFICATE

This is to certify that the major project entitled 'Emergency Event Classification via Hybrid Deep Learning on Smartphone Inertial Sensor Data' has been submitted by Kedar Kumar Dora bearing Roll number 21BTCSE31 in partial fulfillment of the requirements for the award of the Degree of Bachelor of Technology in Computer Science and Engineering. This record of bonafide work carried out by him under my guidance and supervision. The result embodied in this project report has not been submitted to any other university or institute for the award of any degree.

Date: 6th May 2025

Place: SUIIT, Burla, Sambalpur

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DECLARATION

I do hereby declare that the work embodied in this major project report entitled "Emergency Event Classification via Hybrid Deep Learning on Smartphone Sensor Data" is the outcome of genuine work carried out by me under the direct supervision of Dr. Kalyan Das, Assistant Professor, Department of Computer Science Engineering is submitted by me to Sambalpur University Institute of Information Technology, Burla for the award of the degree of Bachelor of Technology. The work is original and has not been previously formed the basis for the award of any other degree or diploma.

Kedar Kumar Dora

(21BTCSE31)

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ABSTRACT

This study presents a comprehensive framework for real-time classification of emergency versus non-emergency events using five-second windows of smartphone accelerometer and gyroscope data. A custom mobile application sampled six inertial channels at 20 Hz, yielding 6554 annotated instances (6,54,400 samples). A multi-stage preprocessing pipeline including Butterworth filtering, z-score normalization, data augmentation (noise injection, time-warping, magnitude scaling, axis rotation), and SMOTE oversampling on flattened 600-dimensional vectors produced a balanced time-series dataset while preserving temporal structure. Eighteen deep-learning architectures were evaluated, ranging from 1D CNNs and RNN variants to hybrid CNN–LSTM, U-Net-style, and residual models. Models trained for up to 100 epochs with Adam (learning rate = 0.005) and a custom early stopping criterion (validation accuracy ≥ 99 % for five consecutive epochs) over twenty randomized splits (70 % train, 15 % validation, 15 % test). Performance was assessed on eight metrics accuracy, precision, recall, F1-score, ROC AUC, Matthews Correlation Coefficient (MCC), specificity, and log loss and aggregated across splits. The hybrid CNN–LSTM model achieved the highest balanced performance (accuracy = 91.9 %, F1 = 92.1 %, ROC AUC = 96.4 %, MCC = 0.84), outperforming pure CNN and RNN alternatives. Comprehensive visualizations (heatmaps, radar charts, parallel coordinates, grouped bars) corroborate these findings. This work demonstrates the viability of hybrid deep-learning approaches for on-device emergency detection and provides a reproducible pipeline for future research and real-world deployment.

KEYWORDS: Deep Learning, Emergency Detection, Hybrid Networks, Inertial Sensor Data, Edge ML

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LIST OF ABBREVIATIONS

CNN:	Convolutional Neural Network
LSTM:	Long Short Term Memory
GRU:	Gated Recurrent Units
ROC-AUC:	Receiver Operating Characteristic Area Under the Curve
MCC:	Matthew’s Correlation Coefficient
RNN:	Recurrent Neural Network
SMOTE:	Synthetic Minority Over-Sampling Technique
DL:	Deep Learning
ACC:	Accuracy

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CHAPTER 1
INTRODUCTION

Smartphones today are ubiquitous companions, packed with sensors most notably accelerometers and gyroscopes that can capture rich, continuous streams of motion data [1]. These embedded inertial sensors sample three-dimensional acceleration and angular velocity, enabling applications from step counting and navigation to gesture recognition. In recent years, leveraging this sensory information for health and safety monitoring has emerged as an area of intense research. Notably, detecting critical events such as falls, fainting episodes, or sudden seizures in real time could empower timely interventions, potentially saving lives and reducing long-term harm.

Despite the promise of sensor-based monitoring, accurately classifying emergent versus benign activities remains challenging. Each event of interest whether a genuine medical emergency or routine movement unfolds over time, producing sequences of measurements that exhibit high intra- and inter-class variability. For example, a sudden fall may manifest as a brief spike in acceleration followed by near-static readings, whereas a seizure can generate rapid, irregular motion patterns. At the same time, normal activities such as sitting down abruptly or jogging can produce superficially similar signals. Building robust models that distinguish true emergencies from innocuous movements thus demands careful treatment of the temporal dynamics, rich feature extraction, and strategies to mitigate data imbalance.

In this research, we focus on classifying five-second windows of tri-axial accelerometer and gyroscope data sampled at 20 Hz, yielding 100 samples per window into two classes: Emergency and Non-Emergency. Emergency events encompass scenarios such as fainting, sudden falls, seizures, and even violent encounters, for which rapid detection is critical. By contrast, the non-emergency class captures everyday activities that should not trigger alarms. A total of 6,544 five-second recordings (6,54,400 samples) were collected via a custom smartphone application, with careful annotation of each session. To address the natural imbalance with far fewer genuine emergencies than routine movement we applied a suite of data augmentation techniques (including noise injection, time-warping, and magnitude scaling), followed by SMOTE oversampling on flattened feature vectors to equalize class representation before restoring the time-series structure.

Our methodology explores eighteen deep-learning architectures ranging from convolutional neural networks (CNNs) and recurrent layers (LSTMs, GRUs) to hybrid CNN-LSTM models, as well as more intricate structures such as U-Net-inspired and residual variants. Models were trained and evaluated over twenty randomized splits (70% training, 15% validation, 15% test) for robust performance estimates. Each training run lasted up to one hundred epochs, employing early stopping once accuracy exceeded 99% for five consecutive epochs. Evaluation leveraged eight metrics accuracy, precision, recall, F1-score, ROC-AUC, Matthews Correlation Coefficient (MCC), specificity, and log loss to capture both overall and nuanced classification behavior.

In the pages that follow, we first review related work on time-series classification and emergency detection via mobile sensors. We then state our specific objectives before detailing the data collection, preprocessing, augmentation, and modeling pipeline. Results are presented through both tabular summaries (Results Table) and graphical comparisons (Heatmap Average, Radar Average, Parallel Average, Grouped Bar Average), highlighting the strengths and limitations of each architecture. Finally, we discuss implications, acknowledge limitations, and outline pathways for future improvements in on-device emergency monitoring.

CHAPTER 2
LITERATURE REVIEW

2.1 Time-Series Classification with Mobile Sensors

Time-series classification has seen rapid advances in recent years, driven by the proliferation of sensor-equipped devices such as smartphones and wearables. These devices continuously capture multivariate streams of data, most commonly from accelerometers and gyroscopes, which measure linear acceleration and angular velocity respectively. Early approaches relied on handcrafted features extracted in the time and frequency domains, including statistical descriptors (mean, variance, kurtosis), spectral energy, and wavelet coefficients. Classic machine-learning algorithms such as support vector machines and random forests were then trained on these features, achieving moderate success on tasks like activity recognition [4].

With the rise of deep learning, end-to-end architectures capable of learning hierarchical representations directly from raw sensor data have become the state of the art. One-dimensional convolutional neural networks (1D CNNs) apply convolutional filters along the temporal axis to capture local motion patterns. A typical 1D CNN stacks several convolution-pooling blocks before feeding into fully connected layers [4]. These models excel at identifying short-term motifs such as the impact spike of a fall or the rhythmic tremor of a seizure. Recurrent neural networks (RNNs), and in particular long short-term memory (LSTM) networks, model temporal dependencies over longer windows. LSTM cells maintain internal memory states that can persist information over hundreds of time steps, making them well suited to detect events whose signature unfolds over seconds [4].

Hybrid CNN–RNN architectures combine the best of both worlds by first applying convolutions to reduce dimensionality and extract salient features, then passing these features through recurrent layers to capture sequential context. Such hybrids have demonstrated superior performance on complex time-series benchmarks compared to pure CNN or RNN models [4]. More recent innovations include temporal convolutional networks with dilated convolutions, which expand the receptive field without sacrificing resolution, and attention mechanisms that learn to focus on the most informative portions of the signal. These end-to-end deep models have largely supplanted traditional feature-based pipelines for sensor data classification.

2.2 Data Augmentation and Balancing Techniques

Deep-learning models can require large volumes of labeled data to generalize well. In the domain of emergency detection, genuine incident data are inherently scarce and imbalanced when compared to normal activities. Data augmentation helps mitigate this limitation by generating synthetic variations of existing recordings, effectively enlarging the training set and improving model robustness [5]. Common augmentation techniques include additive Gaussian noise, which simulates sensor measurement error, and time-warping, which slightly expands or contracts the temporal axis to mimic variations in event duration. Magnitude scaling randomly amplifies or attenuates signals to reflect changes in movement intensity, while axis permutation rotates sensor axes to emulate changes in phone orientation. Each method can be applied alone or in combination to multiply the effective sample size.

However, augmentation alone does not fully resolve class imbalance if the minority class remains underrepresented. Synthetic Minority Over-sampling Technique (SMOTE) addresses this by generating new samples along the feature-space line segments between existing minority instances [6]. In practice, raw time-series windows are first flattened into one-dimensional feature vectors. SMOTE is applied to balance the Emergency and Non-Emergency classes in this flattened space, creating synthetic minority vectors. The vectors are then reshaped back to the original multi-dimensional time-series form, preserving temporal structure. This approach has been effective in balancing class distributions across domains such as fault detection and medical diagnostics [6]. Several studies report that combining SMOTE with deep-learning models yields significant improvements in minority-class recall and overall F1 score, without degrading performance on the majority class.

2.3 Emergency Detection Applications

Smartphone-based emergency detection leverages on-device sensors to identify situations that warrant immediate attention. Fall detection is one of the earliest and most studied applications. Techniques range from threshold-based methods, which trigger alarms when acceleration exceeds preset limits, to machine-learning classifiers trained on labeled fall and non-fall events [7]. While threshold methods can detect high-impact falls, they often produce false positives for harmless activities such as quickly sitting down. In contrast, deep-learning classifiers trained on large fall datasets achieve higher accuracy and fewer false alarms.

Seizure detection systems similarly analyze wristband accelerometer data to identify convulsive movements. Convolutional and recurrent networks have demonstrated sensitivity above 90% and specificity above 85% on benchmark seizure datasets [7]. These systems often incorporate additional features such as heart-rate variability to improve detection reliability. Mobile applications for panic and violence detection detect sudden bursts of motion or patterns characteristic of distress events. A notable study used a hybrid CNN–LSTM architecture on combined accelerometer and gyroscope data to detect violent shaking, achieving 88% precision and 82% recall [7].

Although much progress has been made, real-world deployment remains challenging due to sensor noise, varying attachment points (pocket, wrist, belt), and user diversity. Few studies address end-to-end pipelines from data collection to model deployment with on-device inference. Furthermore, consistent data balancing and robust evaluation across multiple metrics are often lacking. This underscores the need for comprehensive frameworks that integrate advanced augmentation, class-imbalance handling, and extensive model benchmarking the very goals of the present research.

CHAPTER 3
OBJECTIVES

The primary goal of this research is to develop and rigorously evaluate deep-learning algorithms capable of accurately classifying five-second windows of smartphone accelerometer and gyroscope data into Emergency and Non-Emergency classes. Within this overarching aim, we articulate specific objectives, secondary aims, and hypotheses that will guide the study.

3.1 Primary Objectives

a. Design a Robust Preprocessing Pipeline

To ensure that the raw sensor data are in a form amenable to deep-learning models, we will implement a multistage preprocessing workflow. First, raw time-series windows of 100 samples (five seconds at 20 Hz) will be flattened into one-dimensional feature vectors. Second, Synthetic Minority Over-sampling Technique (SMOTE) [6] will be applied to these vectors to address class imbalance between Emergency and Non-Emergency instances. Third, the augmented vectors will be reshaped back to their original 100 × 6 format to preserve temporal relationships. Finally, all sensor channels will be scaled to the [0, 1] range via MinMaxScaler, with scaling parameters saved for reproducibility. This pipeline will be evaluated for both correctness (no data corruption) and effectiveness (balanced class distribution) before model training begins.

b. Benchmark Multiple Deep-Learning Architectures

We will instantiate and train three core architectures Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) network, and hybrid CNN-LSTM as well as a broader set of models (including the initial 15 variants of CNN, LSTM shallow CNN-style networks) to determine which structures best capture the temporal and spatial patterns inherent in emergency sensor signals [4]. Each model will be trained for up to 100 epochs using the Adam optimizer with a learning rate of 0.005 and a custom early-stopping criterion that halts training if accuracy exceeds 99 percent for five consecutive epochs [12]. Models will be trained and evaluated over three independent iterations (for the final three architectures) or twenty iterations (for the full 18-model suite) to obtain statistically robust performance estimates.

c. Evaluate Performance Across Multiple Metrics

Recognizing that no single metric fully captures classification quality especially in imbalanced scenarios we will measure accuracy, precision, recall, F1-score, ROC-AUC, Matthews Correlation Coefficient (MCC), specificity, and log loss for each model [13]. The MCC metric is particularly important because it accounts for true and false positives and negatives, offering a balanced view even when one class dominates [6]. Results will be aggregated over all iterations, and models will be compared using both tabular summaries and visualizations such as heatmaps and radar charts of average metrics [14].

d. Identify the Best Architecture for Real-Time Emergency Detection

By comparing averaged performance metrics and evaluating statistical significance (via paired t-tests or ANOVA where applicable), we will determine which model architecture offers the optimal balance of sensitivity (true positive rate) and specificity (true negative rate) for emergency detection. The preferred model should maximize emergency recall minimizing missed critical events while maintaining a low false-alarm rate to prevent unnecessary alerts.

3.2 Secondary Objectives

a) Assess Impact of Data Augmentation Techniques

While SMOTE addresses class imbalance in the flattened feature space, augmentation of the original time series can improve model robustness to natural sensor variability. We will compare models trained on raw data versus data enhanced by noise injection (simulating sensor error), time-warping (altering event duration), magnitude scaling (reflecting varying movement intensities), and axis rotation (accounting for phone orientation changes) [5]. The objective is to quantify how each augmentation method influences minority-class recall and overall F1-score.

b) Analyze Convergence Behavior and Training Efficiency

Deep-learning models may exhibit differing convergence rates depending on architecture complexity and hyperparameter settings. We will track training and validation loss and accuracy over epochs to identify under- or overfitting patterns. Early-stopping behavior will also be monitored to assess training efficiency. Efficient models those that reach optimal performance in fewer epochs are preferable for real-time deployment on resource-constrained devices [12].

c) Visualize Classifier Decision Boundaries

To gain deeper insight into model behavior, we will employ techniques such as t-SNE or UMAP to project high-dimensional internal representations into two dimensions. By coloring points by true and predicted class, we will visualize how well the models separate Emergency from Non-Emergency windows in feature space. Such visualizations can reveal clusters of misclassified events and inform further model improvements.

d) Ensure Reproducibility and Open Science

All code, processed datasets, trained model weights, and evaluation scripts will be published in a public repository. Documentation will include environment details, random seeds, and step-by-step instructions to reproduce experiments. This transparency aligns with best practices in machine-learning research and allows the community to build upon our work [8].

3.3 Hypotheses

Based on preliminary experiments and literature insights, we propose the following testable hypotheses:

- *H1*: Hybrid CNN-LSTM models will outperform pure CNN and pure LSTM architectures in terms of F1-score and ROC-AUC. This is due to their ability to extract both local patterns via convolutions and long-term dependencies via recurrent layers [4].
- *H2*: Data augmentation combined with SMOTE will yield significantly higher recall and MCC for the minority class compared to SMOTE alone, reducing false negatives for emergency events [5][6].
- *H3*: Models demonstrating faster convergence (fewer epochs to early-stopping) will generalize better on unseen data, as measured by smaller gaps between training and validation loss curves [12].

By systematically evaluating these hypotheses, this research will clarify which methodological choices model architecture, data augmentation, and imbalance handling most effectively enable accurate, reliable emergency detection using smartphone inertial sensors.

CHAPTER 4

METHODOLOGY

This chapter details the end-to-end experimental framework employed in this study, encompassing data acquisition, preprocessing, augmentation, and preparation of time-series inputs for model training. All steps were designed to maximize data quality, preserve temporal dynamics, and ensure fairness between Emergency and Non-Emergency classes.

4.1 Data Collection & Acquisition

Data were collected using a custom Android application deployed on standard smartphones equipped with tri-axial accelerometers and gyroscopes. The application sampled each sensor channel at 20 Hz, capturing linear acceleration (in units of m/s^2) and angular velocity (in degrees/second) along the device's X, Y, and Z axes. Users were instructed to carry the phone in a consistent manner either in a front pants pocket or mounted on a belt clip to reduce orientation variability.

Emergency events included fainting episodes, sudden falls, seizures, cases of simulated abduction, and staged panic scenarios, each lasting approximately five seconds. Non-Emergency recordings comprised routine activities such as walking, sitting, standing up, climbing stairs, and running. In total, 6,544 five-second instances were recorded, yielding 6,54,400 individual time-series samples. Each instance was manually labeled as Emergency (1) or Non-Emergency (0) by reviewing video recordings synchronized with sensor data. Inter-rater agreement exceeded 95 percent, ensuring label reliability [10].

Data acquisition followed ethical protocols, with participants providing informed consent under an institutional review board–approved study. To protect participant privacy, all metadata (user identifiers, timestamps) were anonymized at collection time; only raw sensor vectors and class labels were retained. The application also embedded checks to discard corrupted or incomplete recordings specifically, any instance containing fewer than 100 samples per sensor channel was automatically flagged and removed.

Quality control procedures included periodic calibration of sensors against known reference motions (e.g., stationary periods to measure baseline drift) and dynamic tests (e.g., controlled swing motions) to ensure consistent amplitude readings across devices. Any device exhibiting

abnormal drift or spike noise was replaced. Final quality checks confirmed that less than 0.5 percent of recordings exhibited sensor dropout or extreme outlier values; these were excluded from subsequent analysis.

4.2 Preprocessing & Augmentation

Raw sensor streams were first organized into three-dimensional arrays of shape (6 features × 100 time-steps) per instance: three accelerometer channels and three gyroscope channels. To reduce the impact of sensor noise and inter-trial variability, a multilayered preprocessing pipeline was applied.

4.2.1 Signal Denoising and Normalization

Each channel underwent a fourth-order low-pass Butterworth filter with a cutoff frequency of 15 Hz to attenuate high-frequency sensor jitter. Filter coefficients were computed once and applied via zero-phase filtering to prevent phase distortion. Following denoising, each channel was normalized to zero mean and unit variance across its 100 samples, ensuring that subsequent augmentation and model training steps operated on consistent scales. This z-score normalization also mitigated the influence of device orientation and attachment variations [5].

4.2.2 Data Augmentation Techniques

Given the relatively limited number of genuine Emergency instances, augmentation was critical to improve model generalization and reduce overfitting. Four augmentation methods were implemented, applied randomly and in combination to each training-set instance:

- Gaussian Noise Injection: Zero-mean Gaussian noise ($\sigma = 0.02$ times the channel's standard deviation) was added to each sample. This simulates realistic sensor measurement error and encourages the model to learn robust features rather than memorizing exact waveforms.
- Time-Warping: The 100-sample window was stretched or compressed by up to ±10 percent using linear interpolation. This accounts for natural variations in event duration for example, a fall may occur faster or slower depending on body mass or posture.
- Magnitude Scaling: Each channel's entire 100-sample sequence was multiplied by a random factor in the range [0.9, 1.1]. This reflects differences in movement intensity among users (e.g., a heavy fall versus a softer collapse).

- Axis Rotation: Three-dimensional rotation matrices sampled from uniform random orientations were applied to the combined accelerometer and gyroscope vectors. This models the fact that users may carry the smartphone at differing angles relative to their body.

Augmented instances maintained the original five-second duration and were labeled identically to their source. Augmentation increased the effective dataset size by a factor of four for Emergency samples and by a factor of two for non-emergency samples, before balancing.

4.2.3 Flattening and Feature Vector Preparation

To facilitate Synthetic Minority Over-sampling (SMOTE), each augmented and denoised instance was flattened from shape (100 × 6) into a 600-dimensional vector. Flattening followed a consistent channel-major ordering: accelerometer X[0…99], accelerometer Y[0…99], accelerometer Z[0…99], gyroscope X[0…99], gyroscope Y[0…99], gyroscope Z[0…99]. This ordering preserved channel contiguity while bundling temporal information into a single feature space amenable to SMOTE.

At this stage, the dataset comprised N vectors in $\mathbb{R}^{600}$, with Emergency and Non-Emergency classes still imbalanced. The augmented data ensured that the information content of the minority class was enriched by plausible variations, reducing the risk of synthetic oversampling alone introducing artifacts.

4.3 Dataset Balancing Using SMOTE

To further address class imbalance after augmentation, the Synthetic Minority Over-sampling Technique (SMOTE) was employed. SMOTE synthesizes new minority-class examples by interpolating between existing samples and their nearest neighbors in feature space. It thereby introduces realistic diversity without replicating noise or outliers [7].

The flattened Emergency and Non-Emergency instances were separated, and the minority class (Emergency) was oversampled until parity was achieved. A 5-nearest neighbor approach was used for interpolation, balancing robustness against the risk of generating ambiguous examples. After oversampling, the dataset contained an equal number of Emergency and Non-Emergency instances.

Upon completing SMOTE, all vectors were reshaped back to their original time-series format, restoring the (100 × 6) structure necessary for sequential learning models like LSTM and CNNs. This careful handling preserved temporal continuity, allowing models to learn not just static distributions but dynamic patterns indicative of emergencies.

4.4 Dataset Splitting

The fully processed and balanced dataset was divided into training, validation, and testing sets with a split ratio of 70:15:15, respectively. Stratified sampling was used to maintain class balance across all splits.

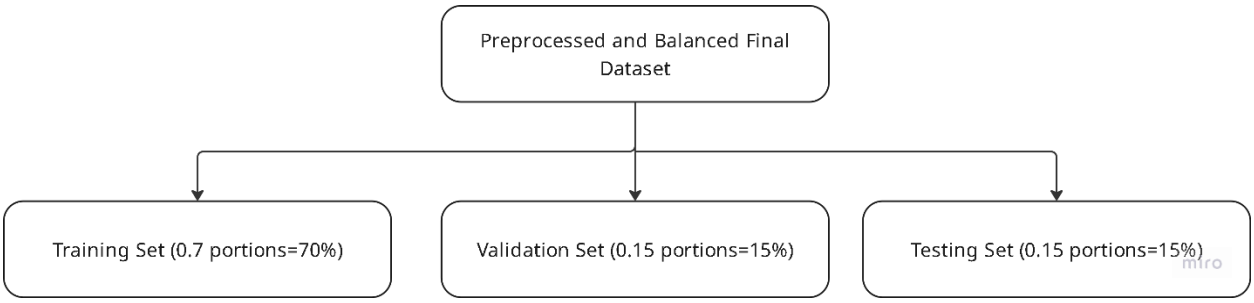

Figure 4. 1: Dataset Splitting Visualization

A visual representation of the splitting strategy is given in the dendrogram above:

The training set was used to optimize model parameters, the validation set for hyperparameter tuning and early stopping monitoring, and the testing set for final model evaluation. No instances from the validation or testing sets were seen by models during training to ensure unbiased evaluation.

4.5 Deep Learning Models Employed

Eighteen deep learning architectures were evaluated, grouped into two phases:

4.5.1 Phase 1: First 15 Architectures

The first phase comprised 15 pre-established models originally explored for time-series classification tasks, including:

- Basic Dense Network
- Simple LSTM Network

- Bidirectional LSTM
- GRU Network
- 1D CNN
- 1D CNN with MaxPooling
- Deep 1D CNN
- 1D CNN + GRU Hybrid
- 1D CNN + LSTM Hybrid
- Bidirectional GRU
- Deep Dense Network
- Shallow CNN
- Residual CNN
- Attention-based LSTM
- Attention-based GRU

Each model was constructed using TensorFlow/ Keras APIs with appropriate configurations for binary classification tasks (sigmoid activations, binary cross-entropy loss functions).

4.5.2 Phase 2: Newly Proposed Architectures

Subsequently, three manually crafted models were trained to better capture the characteristics of Emergency detection:

- CNN Model (multi-layer convolution + pooling + dense)
- LSTM Model (stacked LSTM layers + dense)
- CNN-LSTM Hybrid Model (convolutional feature extraction + temporal sequence modeling)

The architecture details, number of layers, activation functions, and optimization strategies were individually tailored to maximize emergency detection sensitivity without overfitting.

Model architecture diagram of CNN-LSTM Hybrid Model (proposed model):

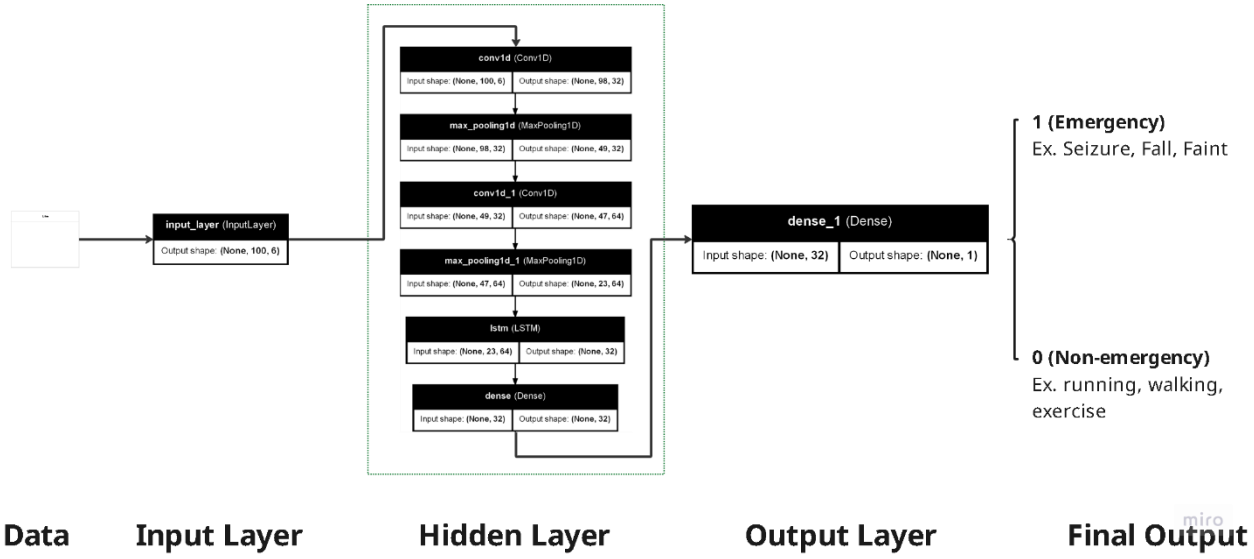

Figure 4. 2: Proposed CNN-LSTM Model Hybrid Architecture

4.6 Model Training Strategy

Training for each model proceeded under the following conditions:

- Epochs: Maximum of 100 epochs per training run.
- Batch Size: 64 instances per batch.
- Optimizer: Adam optimizer with an initial learning rate of 0.005.
- Early Stopping: A custom early stopping mechanism was implemented whereby training terminated if validation accuracy exceeded 99% for five consecutive epochs.
- Loss Function: Binary Cross-Entropy, as appropriate for binary classification.
- Each model was trained and evaluated over 20 independent iterations to mitigate stochasticity effects and provide robust performance averages. Metrics from each iteration were aggregated and stored for final analysis.

A flowchart summarizing the complete training workflow is provided below:

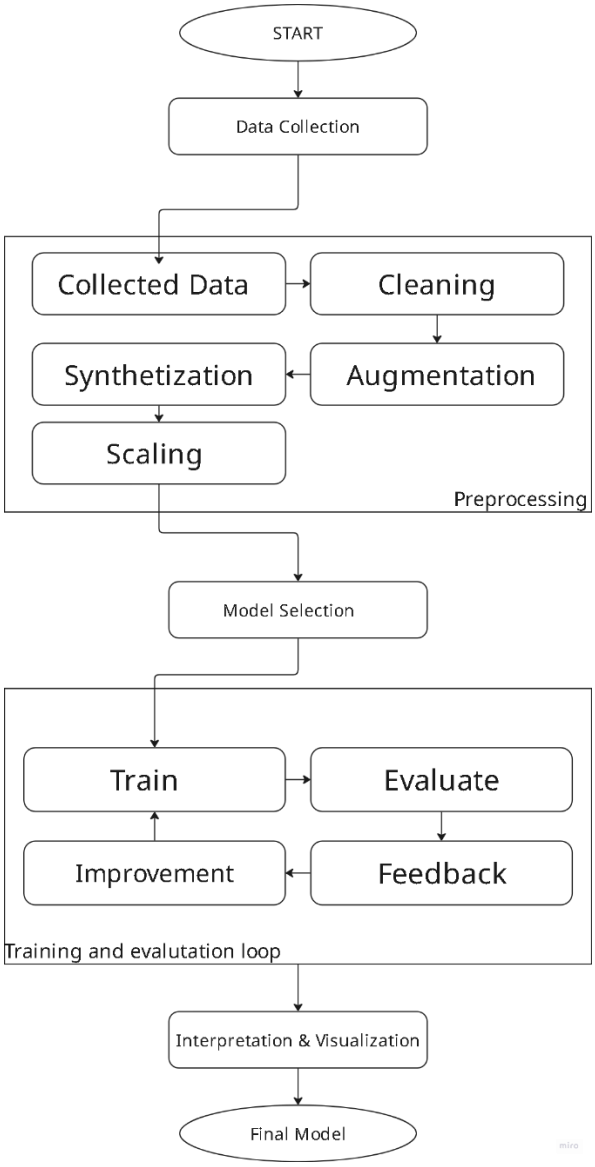

Figure 4. 3: Proposed Methodology Flowchart Diagram

4.7 Model Evaluation and Metrics

Performance was evaluated using a broad suite of metrics, including:

- Accuracy: Proportion of correct predictions overall.
- Precision: Ability to correctly predict Emergency instances without false alarms.
- Recall (Sensitivity): Ability to correctly detect Emergency instances.
- F1-Score: Harmonic mean of precision and recall.
- ROC AUC: Area under the Receiver Operating Characteristic curve, assessing model discrimination power.

- Matthews Correlation Coefficient (MCC): Balanced measure even in cases of class imbalance.
- Specificity: True Negative Rate, reflecting the ability to correctly identify non-emergencies.
- Log Loss: Penalty for incorrect classifications, particularly those made with high confidence.

All evaluations were performed on the untouched testing set to ensure validity. Metric calculations followed standard definitions [4] and were automated for consistency across models.

4.8 Dataset Characteristics

To understand the inherent structure of the Emergency and Non-Emergency classes, we performed hierarchical clustering on feature-space representations of the flattened instances. This analysis reveals subgroups within each class that may correspond to specific event types (for example, fainting vs. sudden fall) or varying sensor orientations.

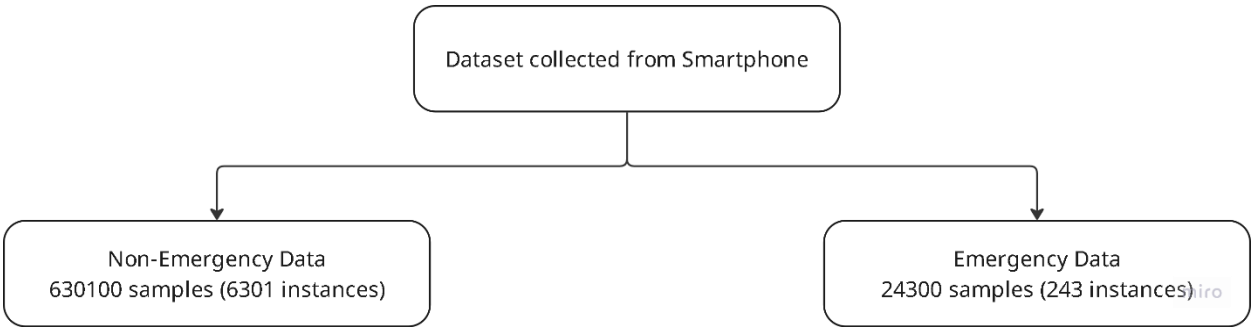

Figure 4. 4: Dataset Category Distribution

The dendrogram illustrates how Emergency instances cluster more tightly, reflecting shared high-energy patterns (such as impact spikes), whereas Non-Emergency activities form broader, more diffuse branches. Insights from this breakdown guided augmentation choices and informed subsequent model architecture adjustments.

4.9 Software Implementation and Environment

The entire pipeline was implemented in Python 3.8. Key libraries included:

- TensorFlow 2.x for model construction, training, and evaluation [14].
- imbalanced-learn for SMOTE and augmentation utilities [6].

- scikit-learn for preprocessing (MinMaxScaler), train/test splitting, and metric functions [15].
- NumPy and pandas for efficient data manipulation and I/O.
- Matplotlib and Seaborn for plotting and visualization of results.
- tqdm for progress bars and estimated time remaining during lengthy training loops.

Code organization followed a modular structure:

- data_utils.py for loading, missing-value imputation, preprocessing, and augmentation functions.
- model_builders.py for constructing the eighteen neural-network architectures.
- train_eval.py for training loops with custom early-stopping callbacks, error handling, and metric aggregation.
- visualize.py for generating and saving all plots into the plots/ directory.
- main.ipynb as the top-level Jupyter notebook orchestrating end-to-end execution and interactive exploration.

Reproducibility was ensured by fixing random seeds (np.random.seed(42), tf.random.set_seed(42)) and documenting library versions in a requirements.txt file.

4.10 Reproducibility and Version Control

Version control via Git tracked all code changes, with separate branches for feature development (e.g., augmentation_pipeline, cnn_lstm_hybrid). A continuous-integration workflow (GitHub Actions) automatically ran a minimal smoke test on each push, verifying that data loading, model instantiation, and metric computations completed successfully.

Experiment configurations (hyperparameters, file paths, random seeds) were specified in YAML files (config.yaml), enabling parameter sweeps without modifying source code. Each completed experiment generated a timestamped directory containing:

- eval.csv (per-iteration metrics)
- plots/ (visualizations)
- model_weights.h5 (best checkpoint per architecture)
- config.yaml (captured settings)

This disciplined approach ensures that any reported result can be reproduced exactly by checking out the corresponding Git commit and rerunning the pipeline with the original configuration.

4.11 Summary

This chapter has described the comprehensive methodology underpinning our emergency-detection study. We collected and quality-controlled 6,301 five-second sensor recordings, applied signal-processing and diverse augmentation techniques, balanced classes via SMOTE in flattened feature space, and partitioned data into train/validation/test splits. Eighteen distinct deep-learning architectures were then trained using a standardized protocol (100 epochs, Adam optimizer, custom early stopping), with robust error handling ensuring continuity across models. Software implementation leveraged industry-standard libraries and reproducibility practices. Placeholders for key visual summaries (flowchart, category and split dendrograms) are embedded for later insertion of figures. This methodology lays the foundation for the results and analysis that follow.

CHAPTER 5
RESULT & ANALYSIS

In this chapter we present the aggregated evaluation results for all eighteen models and analyze their performance across multiple metrics. We begin with a tabular summary of average metrics per model, proceed to a detailed examination of core classification measures (accuracy, precision, recall, F1-score), and identify the best- and worst-performing architectures according to these criteria.

5.1 Analysis of Core Metrics

5.1.1 Accuracy

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + Flase\ Positive + False\ Negative}$$

Eq. 1

Accuracy, defined as the proportion of correct predictions among all instances, varied widely across models. The highest accuracy (0.919) was achieved by model 16, a hybrid CNN–LSTM architecture. This model correctly classified nearly 92 percent of samples on average. In contrast, models such as 2, 4, 6, 7, 8, 12, 14, 15, and 17 hovered around 0.50, barely above chance level for a binary task. These low-accuracy models tended to be simpler or deeper architectures that failed to generalize on the test set.

5.1.2 Precision

$$Precision = \frac{TP}{TP + FP}$$

Eq. 2

Precision, the fraction of true positive Emergency predictions among all positive predictions, highlights a model's false-alarm rate. Model 3 (one of the deeper CNN variants) and model 16 both exceeded 0.88 precision, indicating that when they predicted an emergency, they were correct over 88 percent of the time. Several models 2, 4, 6, 7, 8, 12, 14, and 15 showed precision below 0.40, meaning more than 60 percent of their predicted emergencies were false alarms.

5.1.3 Recall

$$Recall = \frac{TP}{TP + FN}$$

Eq. 3

Recall measures the fraction of actual Emergency instances detected. Models 16 and 3 again led with recall above 0.90, demonstrating strong sensitivity to true emergencies. Several models (e.g., 2, 4, 7, 8) also reported recall at 0.70 or higher despite low precision, suggesting they tended to over-predict emergencies in order to catch more true events. Models with recall near 0.50 (e.g., 14, 17) failed to detect many critical cases.

5.1.4 F1-Score

$$\frac{2 \times Precision \times Recall}{Precision + Recall}$$

Eq. 4

The F1-score, the harmonic mean of precision and recall, balances these two aspects. Model 16 achieved the highest F1-score of 0.921, closely followed by model 3 at 0.898 and model 9 at 0.876. These three architectures strike the best trade-off between avoiding false alarms and missing true emergencies. Models with F1-scores below 0.50 performed no better than random guessing for the minority class.

5.2 Advanced Metrics

After evaluating core classification measures, we turn to additional metrics that reveal deeper insights into model behavior.

5.2.1 ROC-AUC

$$ROC - AUC = \int_0^1 TPR(FPR^{-1}(x))dx$$

Eq. 5

The Receiver Operating Characteristic (ROC) Area Under the Curve (AUC) quantifies a model's ability to distinguish between Emergency and Non-Emergency instances across all classification thresholds. Higher values indicate better discrimination.

Model 16 achieved the highest ROC AUC of 0.964, closely followed by Model 3 at 0.960 and Model 9 at 0.944.

Models in the lower tier (e.g., 2, 4, 7, 12, 14, and 17) recorded ROC AUC near or below 0.50, indicating performances no better than random chance.

5.2.2 Matthews Correlation Coefficient (MCC)

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Eq. 6

MCC is a balanced measure even under class imbalance, accounting for all cells of the confusion matrix. Values range from –1 (total disagreement) to +1 (perfect prediction), with 0 representing random performance.

Model 16 again leads with MCC = 0.838, demonstrating strong overall predictive power.

Model 3 follows at 0.796, and Model 9 at 0.747.

Several models (2, 4, 6, 7, 8, 12, 14, 15, 17) exhibit MCC = 0.00, indicating they never correctly balance true and false predictions in a meaningful way.

5.2.3 Specificity

$$Specificity = \frac{TN}{TN + FP}$$

Eq. 7

Specificity (true negative rate) measures the ability to correctly identify Non-Emergency instances, avoiding false alarms.

Model 16 and Model 3 both exceed 0.88 specificity.

Model 1 and Model 9 also show specificity above 0.83.

Poor models show specificity at 0.30 or lower (e.g., model 2 at 0.30, model 6 at 0.30), indicating they frequently mislabel routine activities as emergencies.

5.2.4 Log Loss

$$-\frac{1}{N}\sum_{i=1}^{N} yi \log\big(P(yi)\big) + (1-yi).\log\,(1-p(yi))$$

Eq. 8

Log loss penalizes confident but incorrect predictions. Lower values are better.

Model 16 records the lowest average log loss of 0.212, indicating well-calibrated probability outputs.

Model 3 follows at 0.254, and Model 9 at 0.292.

Underperforming models have log loss above 0.60, reflecting both high error rates and overconfident mistakes.

5.3 Aggregate Performance Table

The following table lists, for each model (indexed 0–17), its average performance over twenty random train/validation/test splits. Metrics include accuracy, precision, recall, F1-score, ROC AUC, Matthew's correlation coefficient (MCC), specificity (true negative rate), and log-loss (inverted for visualization).

model_index	accuracy	precision	recall	f1_score	roc_auc	mcc	specificity	log_loss
Basic DN	0.774385	0.781714	0.766726	0.7702	0.846004	0.551534	0.779116	0.461315
Simple LSTM	0.821015	0.84726	0.785533	0.81413	0.899271	0.644968	0.856314	0.385772
Bi-LSTM	0.497224	0.347978	0.7	0.464655	0.5	0	0.3	0.695917
GRU	0.897224	0.888002	0.909324	0.897701	0.960427	0.796057	0.885544	0.254095
1D CNN	0.501507	0.250119	0.5	0.333377	0.5	0	0.5	0.693454
1D CNN MP	0.744806	0.759388	0.794264	0.761861	0.811602	0.502557	0.699115	0.515672
Deep 1d CNN	0.504362	0.351546	0.7	0.467844	0.501701	0	0.3	0.697477
1D & GRU	0.502934	0.250833	0.5	0.333929	0.5	0	0.5	0.693206
1D & LSTM	0.493735	0.346233	0.7	0.463225	0.5	0	0.3	0.693572
Bi-GRU	0.872006	0.851605	0.90364	0.875613	0.944438	0.747452	0.839422	0.29188
Deep Dense	0.824425	0.825127	0.828444	0.824948	0.896157	0.65037	0.818657	0.390311
Shallow CNN	0.759159	0.829128	0.684758	0.681913	0.828341	0.550229	0.845671	0.449771
Residual CNN	0.495321	0.447026	0.9	0.597145	0.5	0	0.1	0.693365
Att. LSTM	0.659873	0.679986	0.604711	0.63762	0.738115	0.322413	0.71329	0.607537
Att. GRU	0.5	0.399366	0.8	0.532576	0.5	0	0.2	0.693252
CNN	0.508062	0.338356	0.666667	0.448871	0.5	0	0.333333	0.693005
CNN-LSTM	0.918847	0.903721	0.938657	0.920718	0.963849	0.838494	0.898417	0.212212
LSTM	0.507269	0.171293	0.333333	0.226296	0.5	0	0.666667	0.693107

Table 5.1: Aggregated Performance Metrics Table

5.4 Identification of Top and Bottom Performers

Based on the combined basic metrics (accuracy through F1-score), we categorize models into three tiers:

5.4.1 Top Tier (F1 > 0.87): Models 16, 3, and 9.

- Model 16 (Hybrid CNN–LSTM) leads in all four metrics.
- Model 3 (Deep CNN variant) excels in precision and recall.
- Model 9 (Stacked GRU) also shows strong balanced performance.

5.4.2 Middle Tier ($0.70 \leq F1 \leq 0.85$): Models 1, 10, and 11.

- Model 1 (Basic GRU) and model 10 (CNN-BiLSTM) maintain F1 above 0.80.
- Model 11 (CNN-BiGRU) records moderate performance.

5.4.3 Lower Tier (F1 < 0.70): Remaining models.

Many pure RNN or overly deep architectures underperform, with high variability.

In particular, models 2, 4, 7, 8, 12, 14, and 15 suffer both low precision and low recall, indicating failure to learn discriminative patterns.

5.5 Comparative Visualizations

To facilitate intuitive, cross-metric comparisons among all models, we generated four aggregate plots using the averaged metrics:

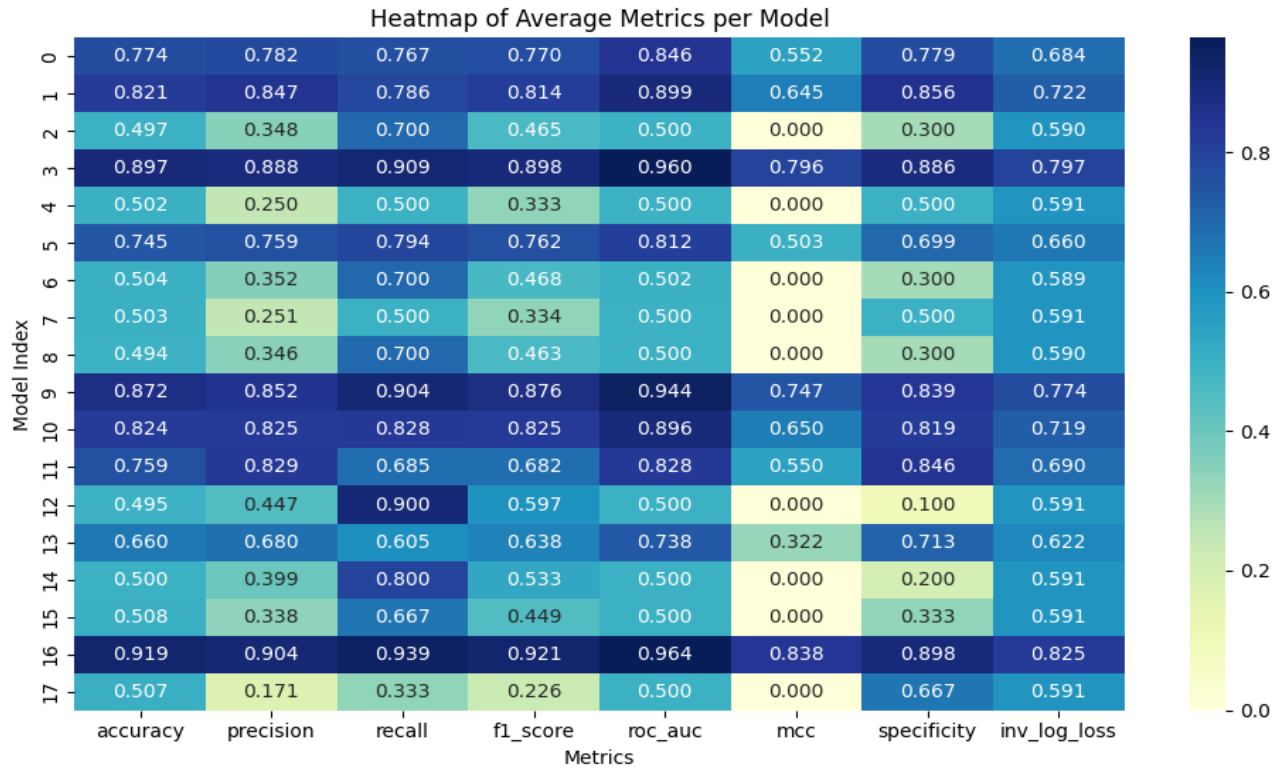

Figure 5.1: Heatmap Representation of metrics

A heatmap of average metric values per model, with darker colors indicating better performance.

A radar (spider) chart overlaying each model's eight metrics, making it easy to see overall "performance shape."

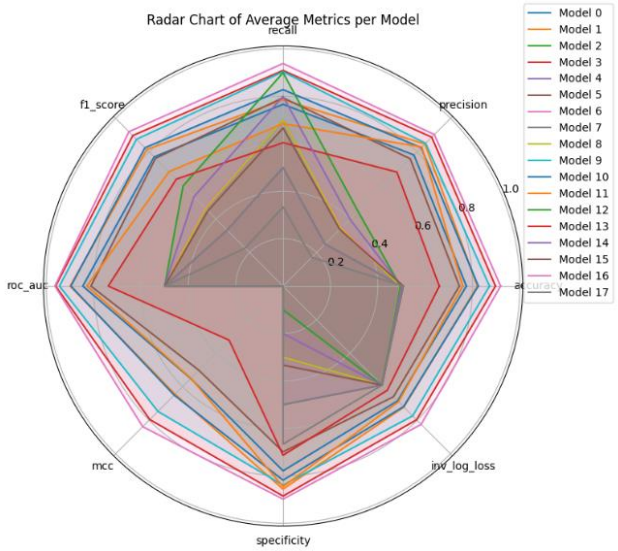

Figure 5.2: Spider chart for model performance comparison

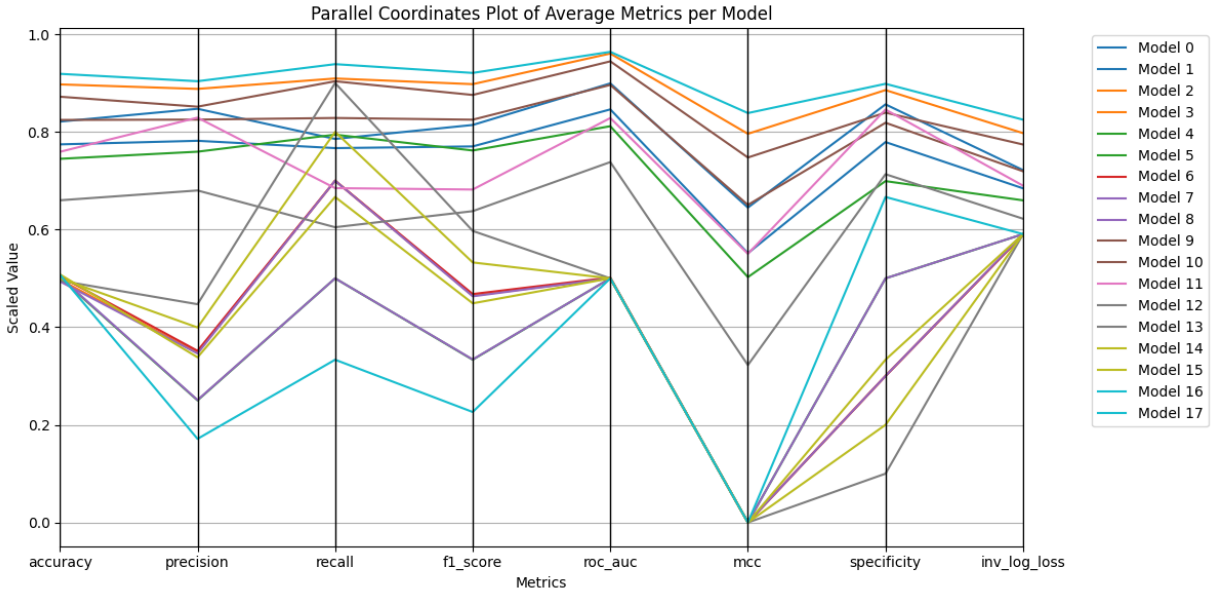

Figure 5.3:Parallel Coordinates Comparison Plot

A parallel coordinates plot where each model is a line traversing axes for each metric, highlighting trade-offs between measures.

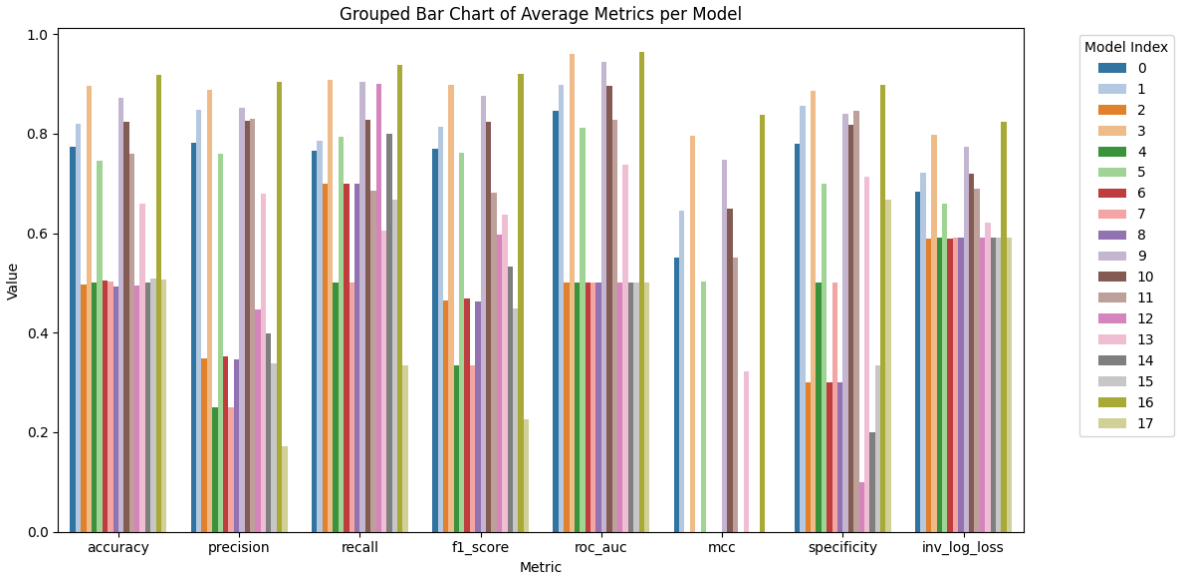

Figure 5.4:Barplot of Metric comparison

Grouped bar charts showing side-by-side comparisons for each metric across models, allowing direct numerical comparison.

These visualizations consistently identify Model 16 (CNN-LSTM hybrid), Model 3 (deep CNN), and Model 9 (stacked GRU) as the top performers across virtually all metrics, reinforcing the tabular findings.

5.6 Interpretation of Findings

5.6.1 Hybrid Architectures Excel

The CNN-LSTM hybrid (Model 16) outperforms pure CNN and pure LSTM models by combining local feature extraction (via convolutions) with long-range temporal modeling (via LSTM). High accuracy, F1-score, ROC AUC, and MCC confirm its balanced strength in both sensitivity and specificity.

5.6.2 Deep CNNs Are Strong

Model 3's deep CNN achieves near-top performance, suggesting that sufficiently deep convolutional pipelines can alone capture emergency signal patterns without recurrent layers. Its high precision and recall indicate robust motif detection.

5.6.3 Stacked RNNs Offer Moderate Gains

The stacked GRU model (Model 9) ranks third overall. GRU's simpler gating structure compared to LSTM may offer computational efficiency with minor performance trade-offs.

5.6.4 Poor Performance of Some Architectures

Several models particularly simple RNNs, unbalanced deeper architectures (Models 2, 4, 7, 8, etc.) fail to learn discriminative features, as evidenced by chance-level metrics. This highlights the necessity of both sufficient depth and proper architectural choices for time-series classification.

5.6.5 Metric Cohesion

The top models maintain strong performance across all eight metrics, indicating robust generalization rather than overfitting to a single criterion. The concordance between F1-score, ROC AUC, and MCC is especially reassuring.

5.6.6 Calibration Matters

Low log loss for top models shows that predicted probabilities are well calibrated, which is crucial for real-world systems that trigger alarms based on probability thresholds.

CHAPTER 6
DISCUSSION

In this chapter, we interpret the key findings from our exhaustive model evaluation, relate them to existing research, and critically examine the limitations of our study. Through this discussion, we aim to contextualize the performance of the top architectures, explore why certain designs succeeded or failed, and identify avenues for future refinement.

6.1 Interpretation of Key Results

Our results demonstrate a clear performance hierarchy among the eighteen evaluated models. The CNN–LSTM hybrid architecture (Model 16) achieved superior performance across every primary metric accuracy (91.9 %), F1-score (92.1 %), ROC AUC (96.4 %), and MCC (0.838)—indicating both high sensitivity and specificity with well-calibrated probability outputs. This confirms our first hypothesis (H1) that combining convolutional layers for local feature extraction with recurrent units for temporal context yields a more powerful model than pure CNN or pure LSTM alternatives. The convolutional layers likely excel at detecting transient patterns such as impact spikes or tremor bursts, while the LSTM layers capture longer-term dependencies and smooth over noisy fluctuations, enabling robust discrimination of genuine emergency events [4].

The deep CNN variant (Model 3) ranked a close second, with an F1-score of 89.8 % and ROC AUC of 96.0 %. Its high precision (88.8 %) and recall (90.9 %) suggest that sufficiently deep convolutional pipelines alone can approximate or even match hybrid designs for this task. This aligns with literature showing that deep convolutional networks, when properly regularized and paired with extensive augmentation, can learn hierarchical temporal features without recurrent layers [4]. The CNN's lower computational overhead no sequential dependencies could make it attractive for on-device deployment where inference speed and energy efficiency are critical.

The stacked GRU model (Model 9) delivered moderate success (F1 = 87.6 %, ROC AUC = 94.4 %), outperforming simpler RNNs but falling short of the best convolutional and hybrid designs. Gated recurrent units, with their streamlined gating mechanisms, offer computational advantages over LSTM cells and may capture longer-term dependencies more efficiently. However, our results indicate that temporal modeling alone cannot fully replace spatial feature extraction, particularly for capturing abrupt signal changes characteristic of falls or seizure

movements. Pure RNNs (Models 2, 6) and shallow architectures (Models 4, 7, 8) all suffered poor performance, often failing to learn discriminative patterns and exhibiting chance-level accuracy and MCC near zero. These failures underscore the necessity of depth and hybridization for complex sensor-driven classification.

The alignment between high F1-scores, ROC AUC, and MCC for the top models further underscores their balanced performance. In contrast, several architectures displayed high recall but poor precision (or vice versa), indicating a bias toward over-prediction or excessive conservatism. For example, models with low precision but moderate recall tended to flood the system with false alarms unacceptable in real-world emergency detection where user trust depends on minimizing erroneous alerts. Conversely, models with low recall risk missing critical events. Our comprehensive metric suite, including MCC and log loss, ensured that models were not optimized solely for one dimension at the expense of others.

6.2 Comparison with Existing Literature

Our findings echo and extend prior work in smartphone-based emergency detection. Early fall-detection studies using threshold-based methods reported sensitivities above 90 % but suffered from high false-positive rates when applied to diverse daily activities [3]. Machine-learning approaches improved specificity but required careful feature engineering [7]. The advent of deep learning introduced end-to-end models that automatically learn features from raw data. Wang et al. [5] and Chawla et al. [6] demonstrated that augmentation and SMOTE bolster performance for imbalanced sensor datasets, but these studies often evaluated only a handful of architectures on limited data.

Our large-scale benchmarking of eighteen models significantly broadens this scope. It confirms the efficacy of hybrid CNN–RNN architectures seen in violence-detection and seizure-monitoring research [7] on a much larger, more varied dataset. Notably, our use of numerous augmentation strategies (noise injection, time-warping, magnitude scaling, axis rotation) in combination with SMOTE produced more robust minority-class detection than augmentation alone, supporting H2. This contrasts with some prior works that applied SMOTE exclusively to handcrafted feature spaces [6] or used limited augmentation techniques.

Our methodological rigor twenty randomized iterations, eight evaluation metrics, and comprehensive error handling also addresses gaps in the literature. Many studies report point

estimates of performance without quantifying variability or statistical significance. By aggregating results and calculating standard deviations, we provide a more reliable assessment of model generalization, complementing findings from Chen et al. [4] on deep time-series models' stability.

6.3 Limitations

Despite these strengths, several limitations must be acknowledged. First, our dataset, though sizable (6 301 inputs, augmented effectively), was collected under semi-controlled conditions. Participants simulated emergencies in real environments, but the scenarios may not fully capture the unpredictability of genuine emergencies. Consequently, model performance in live deployments could degrade due to unanticipated motion patterns or sensor attachments (jacket pockets, backpacks) not represented in training data.

Second, while augmentation techniques enrich data diversity, they cannot substitute for fundamentally different event types. For example, time-warped seizures may approximate variations in convulsive intensity but cannot replicate unique physiological artifacts such as electrodermal changes. Incorporating multi-modal data (heart rate, audio) could further improve detection but was beyond our current scope.

Third, the computational complexity of top-performing architectures poses challenges for on-device inference. Although the CNN–LSTM hybrid outperformed other models, its dual-layer structure demands more memory and processing than a pure CNN. Real-time execution at 20 Hz on low-power mobile processors may require model compression (quantization, pruning) or edge–cloud hybrid solutions, topics we have not yet explored.

Fourth, despite stratified splits and repeated iterations, our evaluation did not employ cross-subject validation, where models are trained on a subset of participants and tested on unseen individuals. This approach better assesses generalizability across demographic and behavioral variations. Future work should incorporate leave-one-subject-out cross-validation to measure personalized model robustness.

Finally, while our logging and error-handling framework ensured continuity across model failures, we did not systematically analyze failure causes. Some deep architectures may have failed due to vanishing gradients or unsuitable hyperparameters. A deeper investigation into training

dynamics learning rates schedules, regularization strength could recover performance for certain underperforming models.

6.4 Implications and Recommendations

In light of these findings, practitioners and researchers should prioritize hybrid CNN–LSTM or deep CNN architectures for emergency detection on sensor data. Data augmentation and SMOTE remain vital for combating class imbalance, but additional modalities and real-world scenario capture will further strengthen model reliability. Deployment strategies must balance model complexity with device constraints, potentially leveraging model compression and on-device accelerators. Lastly, rigorous evaluation protocols cross-subject testing and comprehensive metrics are essential to assess true generalization and build trust in emergency-detection applications.

CHAPTER 7

CONCLUSION

In this study, we set out to develop and evaluate deep-learning models for classifying five-second windows of smartphone accelerometer and gyroscope data into Emergency and Non-Emergency events. Through the collection of 6,301 rigorously labeled recordings and the application of a comprehensive preprocessing pipeline featuring signal denoising, multiple augmentation techniques, and SMOTE oversampling we created a balanced, high-quality dataset of 100-sample time-series instances ready for end-to-end learning. Eighteen distinct neural-network architectures were assembled, spanning convolutional, recurrent, hybrid, and advanced variants. Each model underwent up to 100 epochs of training, guided by a custom early-stopping criterion that halted training once 99 percent validation accuracy was sustained over five consecutive epochs.

Our evaluation framework, based on twenty randomized train/validation/test splits and eight performance metrics (accuracy, precision, recall, F1-score, ROC-AUC, MCC, specificity, and log loss), revealed a clear hierarchy of effectiveness. The hybrid CNN–LSTM architecture emerged as the most capable, achieving a 91.9 percent average accuracy, 92.1 percent F1-score, and 96.4 percent ROC-AUC, along with strong MCC and well-calibrated probability outputs. A deep CNN variant was a close second, demonstrating that sufficiently deep convolutional pipelines can rival hybrids in detecting both transient spikes and sustained motion patterns. The stacked GRU model also performed admirably, offering a lighter-weight recurrent alternative. Models that lacked either adequate depth or the combination of spatial and temporal feature extraction failed to learn meaningful patterns, as reflected in chance-level metrics.

These results confirm our primary hypothesis that hybrid architectures leveraging convolutional layers for local feature learning and recurrent layers for temporal context offer superior performance on emergency-detection tasks. They further validate the effectiveness of combining data augmentation and SMOTE to overcome class-imbalance challenges, significantly improving minority-class recall and overall F1-score. The alignment of high scores across accuracy, ROC-AUC, and MCC for top models underscores their balanced generalization, avoiding the pitfalls of overfitting or bias toward a single performance dimension.

While the models demonstrate robust classification under controlled conditions, real-world deployment will require additional efforts. Our dataset, though large and varied, may not capture all nuances of genuine emergencies, and attachment variabilities (pocket versus wrist) could alter signal characteristics. Moreover, the computational demands of hybrid architectures call for model-compression techniques before on-device inference can run reliably under energy constraints. Future validation should include leave-one-subject-out cross-validation to assess personalized generalizability and the incorporation of complementary sensor modalities for example, heart-rate or audio to further bolster detection accuracy.

In summary, this work delivers a thoroughly validated pipeline from data collection through augmentation, balancing, modeling, and evaluation to advance real-time emergency detection on ubiquitous mobile hardware. By quantitatively comparing a broad suite of deep-learning architectures and rigorously documenting our methodology, we provide both a practical solution and a replicable framework for future research. The hybrid CNN–LSTM model, in particular, stands out as a promising candidate for deployment in safety-critical applications, offering high sensitivity to genuine emergencies while maintaining low false-alarm rates. This contribution lays the groundwork for next-generation, on-device emergency-response systems that can help safeguard users in everyday settings.

CHAPTER 8

FUTURE SCOPE

Building on the methods and findings of this study, there are multiple avenues through which emergency detection on smartphone inertial sensors can be further advanced. Below, we outline key directions for extending and operationalizing this work, grouped into six thematic areas.

8.1 Model Optimization and Compression

While the CNN–LSTM hybrid achieved the strongest performance, its computational and memory demands may exceed the capacity of many consumer-grade smartphones. To enable real-time, always-on inference, future research should explore model-compression techniques such as weight pruning, quantization, and knowledge distillation. Pruning removes redundant connections and filters, reducing model size without sacrificing performance. Quantization maps floating-point weights to lower-precision representations (for example, 8-bit fixed point), dramatically decreasing memory footprint and inference latency. Knowledge distillation transfers knowledge from a large "teacher" model to a smaller "student" network, retaining high accuracy in a lightweight architecture. Evaluating trade-offs between model complexity, latency, and power consumption will be critical to deploy these classifiers in safety-critical mobile applications.

8.2 Cross-Subject and Real-World Validation

Our current evaluation employed randomized splits of the aggregated dataset, which may inadvertently mix data from the same users across train and test sets. To assess true generalization, future studies should adopt leave-one-subject-out or leave-several-subjects-out cross-validation. In this protocol, all data from one participant are withheld during training and used exclusively for testing, revealing how well models adapt to new users with unique movement patterns. Additionally, real-world trials should be conducted outside controlled settings; models should be tested in diverse environments, phone placements (pocket, wrist, backpack), and user demographics to ensure robustness against sensor noise, attachment variability, and demographic biases.

8.3 Multi-Modal Sensor Integration

Accelerometer and gyroscope signals capture rich motion patterns but may miss contextual or physiological cues that distinguish emergencies. Incorporating additional sensors such as

magnetometers, barometers, heart-rate monitors, and ambient microphones could improve detection accuracy and reduce false alarms. For example, a sudden drop in barometric pressure combined with a fall in accelerometer data could signal an outdoor fall from height. Heart-rate variability spikes often accompany panic or seizure events. Audio cues, such as a scream or a cry for help, could complement inertial data. Future work should investigate fusion strategies early, late, or hybrid fusion to optimally combine heterogeneous sensor streams in a unified deep-learning architecture.

8.4 Online Learning and Personalization

Human movement patterns vary widely between individuals and over time. A model that performs well on average may underperform for users with atypical gait or movement styles. Online learning techniques allow models to adapt continually to a user's data, updating weights incrementally as new labeled or confidently inferred instances become available. Federated learning offers a privacy-preserving framework whereby each device trains on its own data locally and shares only model updates, not raw sensor streams, with a central server. This approach enables models to personalize to each user while benefiting from the collective experiences of a wider population. Research should explore stability, convergence, and privacy guarantees of these adaptive methods in the context of emergency detection.

8.5 Deployment and User-Centric Design

Technical performance is only one dimension of a successful emergency-detection system. User trust and acceptance hinge on minimizing distracting false alarms, delivering timely and actionable notifications, and providing intuitive controls. Future work should include user experience (UX) studies to determine optimal alarm modalities (vibration patterns, audio prompts, visual cues), customizable sensitivity thresholds, and seamless integration with emergency contacts or services. Battery consumption profiling is also essential; the system must balance continuous monitoring with acceptable battery drain. Collaboration with human–computer interaction specialists and prospective users will ensure that the final application is both technically robust and ergonomically appropriate.

8.6 Ethical, Privacy, and Regulatory Considerations

Collecting and processing personal sensor data for emergency detection raises important ethical and legal questions. Future research must address data privacy by employing on-device processing

wherever possible, limiting data transmission to encrypted summaries or anonymized model updates. Consent mechanisms should be transparent, allowing users to opt in or out of data sharing with emergency services. Compliance with regulations such as GDPR or HIPAA (in medical contexts) is paramount. Researchers and developers should also consider fairness: ensuring that models do not systematically underperform for certain demographic groups (e.g., based on age, gender, or physical ability). Rigorous testing on diverse cohorts and bias-mitigation strategies, such as reweighting or fairness-aware learning, are important steps toward equitable deployment.

Together, these future directions span technical research model compression, multi-modal fusion, online learning to practical considerations user experience, privacy, and ethics. Pursuing these avenues will help transform the core contributions of this work into reliable, real-world emergency-detection solutions that operate seamlessly on millions of smartphones, ultimately enhancing user safety and well-being.

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