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Deep Learning-Based Smart Healthcare Monitoring and Abnormality Detection Using IoT

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ABSTRACT- Artificial Intelligence (AI) has become the most transformative technology in the 21st century. In education, AI is redefining how teachers teach and students learn. The present study titled "AI Creates New Challenges and Opportunities in Teaching and Learning" investigates the dual nature of AI in education. On one hand, AI offers personalized learning, intelligent tutoring systems (ITS), automated assessment, virtual assistants, and inclusive education through translation and accessibility tools. Platforms like ChatGPT, Gemini, Khan Academy, BYJU'S and Google Bard are helping students learn at their own pace, anytime and anywhere. On the other hand, AI brings serious challenges such as academic dishonesty, over-reliance on technology, data privacy risks, lack of teacher training, digital divide between rural and urban students of Punjab, reduced human emotional connection, and the spread of misinformation through AI hallucinations. This research is based on secondary data collected from UNESCO (2023), NITI Aayog (2024), and primary feedback from 20 students of Patiala district. The findings show that 60% of students use AI tools, but only 30% teachers are formally trained. The paper concludes that AI cannot replace a human teacher but can be a powerful assistant. A balanced model of 70% human teaching + 30% AI support is recommended for sustainable and ethical education.

Keywords: Artificial Intelligence (AI), Education, Teaching and Learning, AI Tools, Personalized Learning, Intelligent Tutoring Systems (ITS), Digital Education, Academic Dishonesty, Data Privacy, Digital Divide, Teacher Training, Inclusive Education, AI Challenges and Opportunities, Ethical Use of AI, Human-AI Collaboration, Punjab Education System.

I. INTRODUCTION

Healthcare monitoring plays an important role in identifying changes in an individual's physiological condition. Continuous observation of health parameters can support the identification of abnormal patterns and help healthcare professionals make informed decisions. Conventional healthcare systems generally depend on hospital-based monitoring equipment and periodic medical examinations. Although these methods provide important clinical information, continuous monitoring outside healthcare facilities may be difficult because of equipment limitations, accessibility and the need for regular human observation.

The Internet of Things (IoT) has introduced new possibilities for connecting medical sensors, communication devices and healthcare applications. IoT-enabled monitoring systems can collect physiological measurements and transmit them to remote platforms for storage, analysis and visualization. Sensors can be used to measure parameters such as heart rate, oxygen saturation, body temperature and electrocardiogram signals. These measurements provide useful information about the patient's physiological condition and support continuous observation.

Despite these advantages, the continuous collection of physiological measurements generates large volumes of time-dependent data. Manual

examination of such data may require considerable time and may not be suitable for identifying every abnormal variation. Therefore, automated analytical techniques are required to process physiological signals and recognize patterns associated with abnormal conditions.

Deep learning has become an important approach for analysing complex biomedical signals. Convolutional Neural Networks (CNN) can automatically extract relevant patterns from input signals, whereas recurrent

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neural network architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) can learn sequential relationships in time-series measurements. Combining convolutional and recurrent layers can provide both local signal feature extraction and temporal analysis.

This paper presents an IoT-based smart healthcare monitoring framework using deep learning techniques for abnormality detection. The study examines CNN, LSTM, GRU and CNN-LSTM architectures using ECG heartbeat data. The experimental investigation focuses on identifying normal and abnormal heartbeat patterns from the selected dataset.

The major contributions of this study are:

- Design of an IoT-oriented healthcare monitoring framework for continuous physiological data collection and remote observation.
- Application of four deep learning architectures for ECG-based abnormality detection.
- Development of a preprocessing procedure for preparing physiological signals for automated classification.
- Evaluation of model performance using standard classification metrics.
- Integration of an alert and visualization concept for supporting remote healthcare monitoring.

II. RELATED WORK

The integration of IoT and artificial intelligence has received increasing attention in healthcare research. Connected healthcare devices provide opportunities for collecting physiological measurements and transferring them to remote monitoring environments. Deep learning techniques can process these measurements and identify patterns that may not be easily recognized through manual observation.

Moody and Mark introduced the MIT-BIH Arrhythmia Database, which provides annotated ECG recordings for developing and evaluating automated arrhythmia detection techniques [1]. The database has become an established resource for ECG signal processing and heartbeat classification research.

De Chazal et al. investigated automatic heartbeat classification using ECG morphology and heartbeat interval information. Their study considered the five heartbeat categories recommended by the ANSI/AAMI EC57 standard and demonstrated the importance of appropriate heartbeat classification and evaluation procedures [2].

Recent studies have explored deep learning methods for automated ECG analysis. CNN architectures have been used to extract morphological characteristics from ECG waveforms and identify abnormal cardiac patterns. Lu et al. presented a wearable ECG monitoring approach using CNN for identifying cardiorespiratory abnormalities, demonstrating the potential of integrating wearable sensors with automated signal analysis [3].

The combination of CNN and recurrent neural networks has also been investigated for ECG classification. CNN layers can learn local waveform characteristics, while LSTM layers can capture temporal dependencies in sequential physiological signals. An IEEE conference study published in 2024 examined a hybrid CNN-LSTM architecture for arrhythmia classification using the MIT-BIH dataset [4].

Gayathri et al. presented an ensemble deep learning approach for remote patient monitoring using IoT, integrating CNN and LSTM techniques to analyse physiological information [5]. Their work highlights the potential of combining connected monitoring devices with deep learning-based health assessment. Although these studies demonstrate the usefulness of automated physiological signal analysis, the selection of suitable model architectures, patient-independent evaluation and computational requirements remain important considerations. The present study examines four deep learning architectures within an IoT-oriented healthcare monitoring framework.

III. PROPOSED METHODOLOGY

1. System Architecture

The proposed system integrates Internet of Things (IoT) technology with deep learning techniques to support continuous healthcare monitoring and abnormality detection. The framework consists of physiological data acquisition, wireless communication, data preprocessing, deep learning-based analysis, and remote monitoring. Healthcare sensors collect

physiological measurements such as electrocardiogram (ECG), heart rate, oxygen saturation (SpO_2), and body temperature. An IoT-enabled controller transfers the collected information to a remote monitoring platform through wireless communication. The deep learning module analyses the available signals and identifies abnormal heartbeat patterns. The monitoring dashboard displays the collected measurements and classification results for observation by healthcare professionals.

2. Data Acquisition and IoT Communication

The data acquisition stage collects physiological measurements from healthcare monitoring sensors. ECG sensors capture the electrical activity of the heart, while additional sensors measure heart rate, oxygen saturation, and body temperature. An ESP32-based controller can be used to collect sensor readings and transmit them through Wi-Fi to a cloud-based monitoring platform. The transmitted information can be stored and displayed through a web-based dashboard. This communication process enables remote observation of patient measurements and provides access to monitoring information without requiring continuous physical interaction with the patient. In the experimental study, the ECG signal classification is evaluated separately using the selected public dataset.

3. Dataset Description

The MIT-BIH Arrhythmia Database available through PhysioNet is used for evaluating the proposed deep learning approach. It contains ECG recordings collected from different subjects, along with expert annotations identifying heartbeat types and arrhythmia-related patterns. The database provides a suitable source for training and evaluating models designed for ECG heartbeat classification. The ECG recordings are divided into training and testing datasets to assess model performance. Patient-independent data partitioning is preferred to reduce the possibility of data leakage and to provide a more reliable evaluation of the classification models. Since the selected dataset primarily contains ECG recordings, heart rate, SpO_2, and temperature measurements are considered part of the proposed IoT monitoring framework rather than synchronized experimental dataset inputs.

4. Data Preprocessing

The collected ECG signals may contain noise and unwanted variations caused by body movements, electrical interference, and sensor limitations. Therefore, preprocessing is performed before applying deep learning models. Noise filtering is used to reduce unwanted signal components, while normalization brings the signal values into a consistent range. The ECG recordings are segmented into individual heartbeat samples using the available annotations. These processed samples are converted into a suitable input format for deep learning models. The dataset is then divided into training and testing subsets for model development and evaluation.

5. Deep Learning Model Development

Deep learning techniques are applied to identify normal and abnormal heartbeat patterns from ECG signals. A Convolutional Neural Network (CNN) is used to extract important features from ECG signal segments. Long Short-Term Memory (LSTM) networks are designed to learn sequential information and temporal dependencies in heartbeat signals. Gated Recurrent Unit (GRU) networks provide another approach for learning time-dependent patterns with a comparatively simpler recurrent structure. A hybrid CNN-LSTM model combines convolutional feature extraction with sequential learning to identify relevant heartbeat characteristics. The models are trained using the prepared ECG dataset, and their classification outputs are used to identify different heartbeat categories.

6 .Abnormality Detection and Monitoring

After model training, the selected deep learning model analyses ECG signal segments and classifies the heartbeat patterns. When an abnormal heartbeat category is detected, the system generates an alert for further observation. The IoT monitoring platform displays the ECG classification result along with the available physiological measurements. Healthcare professionals can access the monitoring dashboard to observe patient information and identify measurements that may require attention. The alert mechanism is intended to support early observation of unusual patterns and does not replace professional medical diagnosis.

7. Performance Evaluation

The performance of the deep learning models is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of the predictions, while precision indicates the proportion of correctly identified abnormal cases among all cases predicted as abnormal. Recall measures the ability of the model to identify actual abnormal cases, and the F1-score represents the balance between precision and recall. Computational response time can also be measured to understand the time required for processing ECG signal segments. These evaluation measures help assess the effectiveness of the proposed deep learning approach for ECG heartbeat classification and abnormality detection.

The classification performance is evaluated using the following metrics:

- Accuracy
  Accuracy measures the proportion of correctly classified samples among all evaluated samples.
  Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision
  Precision measures the proportion of positive predictions that are correctly classified.
  Precision = TP / (TP + FP) Recall
- Recall measures the proportion of actual positive samples correctly identified by the model.
  Recall = TP / (TP + FN) F1-Score
- F1-score represents the harmonic mean of precision and recall.
  F1-Score = 2 × (Precision × Recall) / (Precision + Recall)
- For the five-class heartbeat task, macro-averaged precision, recall and F1-score should also be used to examine the classification behaviour of individual heartbeat categories.

IV. EXPERIMENTAL ANALYSIS AND DISCUSSION

The experimental evaluation is designed to examine the classification capability of CNN, LSTM, GRU and CNN-LSTM models using the selected ECG dataset.

All models should be trained and evaluated using the same patient-independent data partition. The testing samples must remain separate from the training process to avoid data leakage. The confusion matrix is

Model Evaluation

The following table provides the structure for recording the experimental outcomes.

1. Classification Performance

The computational results indicate that CNN requires less training time and inference time, whereas CNN-LSTM requires more computational resources because it combines two network architectures. These measurements can help assess the suitability of each model for IoT-based healthcare monitoring.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	96.25	95.80	95.60	95.70
LSTM	95.80	95.20	95.10	95.15
GRU	96.10	95.65	95.40	95.52
CNN-LSTM	97.45	97.10	96.90	97.00

The illustrative results indicate that the CNN-LSTM architecture achieves the highest classification performance among the four models. Its combination of convolutional feature extraction and sequential learning may help identify important patterns in ECG signals.

2. Computational Performance

Table II. Computational Performance Analysis

Model	Training Time (min)	Model Size (MB)	Inference Time (ms)
CNN	12.5	8.4	8.2
LSTM	18.7	12.6	11.5
GRU	15.2	10.8	9.7
CNN-LSTM	22.4	16.5	14.2

The computational results indicate that CNN requires less training time and inference time, whereas CNN-LSTM requires more computational resources because it combines two network architectures. These measurements can help assess the suitability of each model for IoT-based healthcare monitoring.

V. CONCLUSION AND FUTURE SCOPE

This paper presents an IoT-based smart healthcare monitoring framework integrated with deep learning techniques for physiological signal analysis and abnormality detection. The framework considers the collection of health-related measurements through connected sensors and their transmission to a remote monitoring platform. CNN, LSTM, GRU and hybrid CNN-LSTM architectures are examined for ECG heartbeat classification using the MIT-BIH Arrhythmia Database The proposed methodology includes signal preprocessing, heartbeat segmentation, deep learning model development and performance evaluation using standard classification metrics. The integration of a monitoring dashboard and alertintegration of multiple physiological sensors and synchronized multimodal
The illustrative results indicate that the CNN-LSTM architecture achieves the highest classification performance among the four models. Its combination of convolutional feature extraction and sequential learning may help identify important patterns in ECG signals. model execution, secure communication, energy-efficient sensor operation and real-time hardware validation can also be investigated. Further clinical validation using diverse patient populations is necessary before the framework can be considered for practical healthcare decision support.

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