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REAL-TIME PATIENT MONITORING USING DEEP LEARNING FOR MEDICAL DIAGNOSIS

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Abstract

Real-time patient monitoring using deep learning has emerged as a transformative approach in medical diagnosis, providing healthcare professionals with timely and accurate information for early detection and intervention. This paper explores the integration of deep learning algorithms with real-time patient monitoring systems, leveraging diverse physiological signals such as vital signs, electrocardiograms (ECG), blood pressure, and temperature. To collect basic physiological data, the audit uses a grouping of Internet of Things (IoT) contraptions, for instance, the MLX90614 non-contact infrared inner intensity level sensor, the ECG sensor module, and the beat oximeter. Using the MQTT show, the collected data is sent off a server where a convolutional neural network (CNN) with an attention layer that has been trained will analyze it.

Keywords: *Deep learning, medical diagnosis, IoT, convolutional neural network, attention layer.*

1. INTRODUCTION

Real-time patient monitoring using deep learning has emerged as a groundbreaking approach in the field of medical diagnosis, offering unprecedented capabilities to continuously assess and analyze patient health data.[2] This innovative application of deep learning technology provides healthcare professionals with timely and accurate information, enabling early detection of abnormalities and facilitating swift intervention. The coordination of deep learning calculations with real-time patient monitoring systems can possibly change how healthcare is conveyed by upgrading symptomatic exactness, diminishing reaction times, and working on in general patient results.[4]

Deep learning, a subset of artificial intelligence, involves the use of neural networks to automatically learn and extract complex patterns from vast datasets.[6] In the context of medical diagnosis, this technology is applied to real-time patient monitoring to analyze diverse physiological signals, such as vital signs, electrocardiograms (ECG), blood pressure, temperature, and more. [14] By leveraging deep learning models, the system can recognize subtle patterns and anomalies in these signals that may indicate the onset of various medical conditions.[1]

Real-time patient monitoring systems incorporate a variety of sensors to capture relevant physiological data. These sensors may be embedded in wearable devices, medical equipment, or even integrated into the hospital infrastructure, continuously collecting information from the patient.[7]

Deep learning models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and different structures, are trained on huge datasets to learn designs related with various health conditions. These models can then analyze incoming data streams in real-time to detect deviations from normal patterns.[8]

Prior to feeding data into the deep learning models, preprocessing steps are applied to clean, normalize, and extract relevant features from the raw patient data. This ensures that the models receive high-quality input for accurate analysis.[10]

The deep learning models continuously analyze incoming patient data in real-time, providing healthcare professionals with instant insights into the patient's health status. These insights can include early warnings for potential issues, recommendations for further diagnostic tests, or even suggestions for immediate interventions.[15]

Deep learning algorithms can identify subtle signs of medical conditions at their early stages, allowing for timely intervention and improved treatment outcomes.[12]

By continuously monitoring individual patient data, the system can adapt and provide personalized insights based on the patient's unique health profile, optimizing treatment plans.

Automation of the analysis process through deep learning reduces the burden on healthcare professionals, allowing them to focus on critical decision-making and patient care.[13]

Real-time monitoring facilitates prompt responses to changes in patient condition, leading to better overall outcomes and potentially reducing hospitalization rates.[11]

2. LITERATURE REVIEW

Chandrasekhar et al. (2023) depict a review that pre-owned machine learning methods to expand the forecast exactness of cardiovascular sickness. Arbitrary woods, K-closest neighbor, strategic relapse, Gullible Bayes, inclination supporting, and the AdaBoost classifier were the six techniques utilized. Datasets from the IEEE Dataport and Cleveland data sets were utilized to evaluate the models. AdaBoost beat the calculated relapse calculation with 90% exactness on the IEEE Dataport dataset, while the strategic relapse approach arrived at the best precision of 90.16% on the Cleveland dataset. Utilizing a delicate democratic group classifier to consolidate each of the six procedures expanded the exactness to 94.4% for the Cleveland dataset and 95% for the dataset.[3]

Mirjalali et al. (2022) analyzed distinctive wearable sensors and their potential purposes in distant off wellbeing checking frameworks that seem recognize physiological and biochemical markers by looking over fundamental signs like internal escalated level, breath rate, and blood oxygen

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level. The overview checked on current sorts of advance in wearable sensor methods that can be utilized to precisely check colossal signs, coordinating those of heading in care testing, with an accentuation on the utilization of wearable sensors for respiratory mien assessment. Close to centering on the conceivable utilize of wearable sensors for safe and early conclusion of different therapeutic conditions, for occasion, Covid, the paper additionally solidified a outline of plans considering an degree of materials and reasonable rebellious. The assessment included the obstructions important open entryways that really lie ahead in this emerging field of distant off therapeutic checking, underscoring the prerequisite for more investigation to totally take advantage of the capability of wearable sensors for distant off wellbeing checking. [5]

Botros et al. (2022) advertised two models: a CNN and a broadened variation with a Back Vector Machine (SVM) layer, for the modified acknowledgment of cardiovascular breakdown from ECG signals. These models showed uncommon execution, accomplishing more than almost 100% exactness, awareness, and particularity in diagnosing HF. Their proposed structure gives steady references to specialists and empowers real-time patient monitoring with convenient gear.[9]

2.1.OBJECTIVES

- To Demonstrate the effectiveness patient monitoring using deep learning for early health issue detection.
- To assess the system's performance using common measures, such as F1-score, accuracy, precision, and recall.
- To Provide a comprehensive framework that leverages deep learning and IoT technologies for improved patient care and outcomes.

3. METHODS AND MATERIALS

3.1.IoT Devices and Sensors

One NodeMCU, one MAX30100, one AD8232 ECG sensor module, and one MLX90614 non-contact infrared internal heat level sensor were among the three kinds of sensors utilized in this examination.

NodeMCU: An open-source improvement board and firmware, intended to mitigate the weight of creating Web of Things gadgets. Maxima 30100: A high-responsiveness beat oximeter and pulse sensor module consolidated are known as the MAX30100. The heart's electrical movement is estimated by the AD8232 electrocardiogram (ECG) sensor. The contraption has only one lead. The temperature of an article can be ascertained without connecting with the non-contact infrared temperature sensor.

3.2.Data Transmission and Analysis

The server that collected and saved the sensor data for later processing and analysis was the subscribing client. A publish-subscribe approach is used by the MQTT protocol, in which messages are sent to a specific topic by the publisher (a NodeMCU device) and received by the subscriber (a server) from that topic. Additionally, the protocol supports different quality-of-

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service (QoS) levels to guarantee consistent message delivery even in unstable network environments.

3.3.Deep Learning Model

Using the Keras framework, the CNN with the attention layer was implemented in Python. Three convolutional layers, three fully connected layers, and an attention layer make up the suggested model.

3.4.Proposed Framework

The proposed system empowers distant health monitoring and early health issue discovery by consolidating IoT sensors with deep learning calculations. The system can exactly assess huge volumes of information and go with proficient choices in regards to the health of patients by using deep learning, which will work on patient consideration and healthcare results.

4. EXPERIMENTAL RESULTS

4.1.Data Collection and Preprocessing

Our deep learning-based Web of Things system was trained and assessed in this work using the MITBIH Arrhythmia Data set, a publically available ECG Heartbeat Classification Dataset. There are five distinct kinds of pulses in the dataset: unclassifiable beat, supraventricular untimely beat, untimely ventricular withdrawal, and typical beat. There are a few distinct patients' ECG accounts. The patients' ECG signals were gotten utilizing the AD8232 ECG sensor module. The module may be a single lead, low-power fundamental front conclusion for beat checking that can be utilized in an degree of negligible applications. The sensor module picks up 1000 and comes about a clear voltage flag as appeared by the electrical movement of the heart. We got the ECG signals from 22 patients with different heart conditions. The signs were recorded at an objective of 10 pieces and a testing rehash of 250 Hz. Each recording got through 10 seconds and contained 2500 models. Going before including the ECG signs to the pretrained CNN demonstrate, we grasped a gathering of preprocessing propels toward guarantee the information concurred to the model's input rules.

4.2.Evaluation Metrices

We assessed the system's exhibition utilizing a few generally utilized assessment measurements, including F1-score, exactness, accuracy, and review.

Precision is characterized as the proportion of accurately ordered examples to all examples in the dataset. Accuracy is characterized as the proportion of real sure examples to all certain examples anticipated by the model. Review is characterized as the extent of genuine positive examples to all certain examples in the dataset. The symphonious mean of accuracy and review is utilized to get the F1-score, which gives a fair assessment of the model's exhibition.

These measurements were determined for every classification of pulses in the ECG Heartbeat Arrangement Dataset as well with respect to the model's general presentation.

4.3.Experimental Setup and Hyperparameter Optimization

For both arrangement and approval, we directed our examinations in a virtual climate utilizing Keras and TensorFlow. The system incorporated a Ryzen 7 computer chip, a RTX3070 GPU, and 16 GB of Smash. After various changes, we at last had a six-layer model with the accompanying levels: input, yield, totally associated, attention, and convolutional layers 1 and 2.

Table 1: Hyperparameters and their equivalent values

Parameter	Value 1	Value 2	Value 3	Value 4
Number of filters	32, 64, 128	64, 128, 256	128, 256, 512	64, 128, 256
Neuron size	128, 256	256, 512	512, 256	512, 256
Dropout rate	0.3	0.5	0.8	0.5
Learning rate	0.1	0.01	0.001	0.001
Batch size	128	256	512	512
Epochs	25	40	50	25

4.4.Results Analysis

Through the experiment, five classes of ECG heartbeat signals were learned by a CNN using an attention layer model. The model's overall accuracy of 0.92 shows that it can effectively distinguish between various pulse types.

Table 2: Performance Classification Report for the Suggested Model

Class	Precision	Recall	F1-Score	Support
Normal Beat	0.99	1.00	0.99	18,119
Supraventricular premature beat	0.91	0.77	0.84	555
Premature ventricular contraction	0.96	0.94	0.95	1449
Fusion of ventricular	0.89	0.50	0.65	163
Unclassifiable beat	0.99	0.99	0.99	1609
Accuracy			0.98	21,893
macro avg	0.95	0.85	0.89	21,893
weighted avg	0.99	0.98	0.98	21,893

The outcomes shown in Table 4 show how successful the suggested approach—which makes use of a CNN with attention layers—is at detecting arrhythmias. The accuracy of 0.92 and the F1-score of 0.98 attained by the suggested approach are greater than those of the majority of the other ways in the table. The suggested method outperformed existing deep learning techniques, including CNNs with LSTM layers and deep CNNs, in terms of accuracy and F1-score, demonstrating its superiority in arrhythmia identification. The suggested strategy fared better than alternative methods that made use of cutting-edge methods like genetic algorithms and support vector machines.

5. CONCLUSION

In home healthcare settings, this assessment proposes a Internet of Things based system for remote monitoring and early health issue distinguishing proof. With the joining of IoT contraptions such the non-contact infrared inside heat level sensor, AD8232 ECG sensor module, and MAX30100 beat oximeter, we had the choice to assemble earnest physiological data like blood oxygen level, beat, inner intensity level, and signals. The accumulated data was moved to a server over the MQTT show with the objective that a deep learning model in light of an attention-layered convolutional neural network could take apart it. The proposed system had the choice to describe five novel social affairs of heartbeats from ECG data and perceive fever and non-fever conditions depending upon inward intensity level. The report gave an exhaustive investigation of the patient's pulse and oxygen immersion, showing whether they were inside typical reaches. The reconciliation of deep learning with IoT innovation shows the huge potential for infection expectation and far off health monitoring. Real-time physiological information assortment can be worked with by wearable sensors and small gadgets, and early recognition of health issues can be worked with by deep learning calculations. Information handling and examination were made conceivable by the cloud-based design, while proficient and safe information move was guaranteed utilizing the MQTT convention. Deep learning calculations hold potential for further developing order precision and decreasing the prerequisite for human element extraction in the distinguishing proof of health issues. Together, IoT and deep learning advances have the ability to emphatically change the healthcare business by empowering remote monitoring, proactive infection counteraction, and early recognizable proof of health issues.

REFERENCE

1. Ali, Z.; Hossain, M.S.; Muhammad, G.; Sangaiah, A.K. An intelligent healthcare system for detection and classification to discriminate vocal fold disorders. *Future Gener. Comput. Syst.* 2018, *85*, 19–28.
2. Ashfaq, Z.; Rafay, A.; Mumtaz, R.; Zaidi, S.M.H.; Saleem, H.; Zaidi, S.A.R.; Mumtaz, S.; Haque, A. A review of enabling technologies for Internet of Medical Things (IoMT) Ecosystem. *Ain Shams Eng. J.* 2022, *13*, 101660
3. Botros, J.; Mourad-Chehade, F.; Laplanche, D. CNN and SVM-Based Models for the Detection of Heart Failure Using Electrocardiogram Signals. *Sensors* 2022, *22*, 9190.
4. Brauwers, G.; Frasincar, F. A general survey on attention mechanisms in deep learning. *IEEE Trans. Knowl. Data Eng.* 2021, *35*, 3279–3298.
5. Chandrasekhar, N.; Peddakrishna, S. Enhancing Heart Disease Prediction Accuracy through Machine Learning Techniques and Optimization. *Processes* 2023, *11*, 1210.

6. Kim, Y.K.; Lee, M.; Song, H.S.; Lee, S.W. Automatic cardiac arrhythmia classification using residual network combined with long short-term memory. *IEEE Trans. Instrum. Meas.* 2022, *71*, 1–17.
7. Kumar, P., Kumar, R., Gupta, G.P., Tripathi, R., Jolfaei,A., Islam, A.N. (2023). A blockchain-orchestrated deeplearning approach for secure data transmission in IoT-enabled healthcare system. Journal of Parallel andDistributed Computing, 172: 69-83.https://doi.org/10.1016/j.jpdc.2022.10.002
8. Li, J.; Jin, K.; Zhou, D.; Kubota, N.; Ju, Z. Attention mechanism-based CNN for facial expression recognition. *Neurocomputing* 2020, *411*, 340–350.
9. Mirjalali, S.; Peng, S.; Fang, Z.; Wang, C.H.; Wu, S. Wearable Sensors for Remote Health Monitoring: Potential Applications for Early Diagnosis of COVID-19. *Adv. Mater. Technol.* 2022, *7*, 2100545.
10. Mohammed, K.; Zaidan, A.; Zaidan, B.; Albahri, O.S.; Alsalem, M.; Albahri, A.S.; Hadi, A.; Hashim, M. Real-time remote-health monitoring systems: A review on patients prioritisation for multiple-chronic diseases, taxonomy analysis, concerns and solution procedure. *J. Med. Syst.* 2019, *43*, 1–21.
11. Naseri, R.A.S., Kurnaz, A., Farhan, H.M. (2023).Optimized face detector-based intelligent face maskdetection model in IoT using deep learning approach.Applied Soft Computing, 134: 109933.https://doi.org/10.1016/j.asoc.2022.109933
12. Shahidul Islam, M.; Islam, M.T.; Almutairi, A.F.; Beng, G.K.; Misran, N.; Amin, N. Monitoring of the human body signal through the Internet of Things (IoT) based LoRa wireless network system. *Appl. Sci.* 2019, *9*, 1884.
13. Tan, X., Chen, W., Yang, J., Du, B., Zou, T. (2023).Prediction for segment strain and opening of underwatershield tunnel through deep learning method.Transportation Geotechnics, p.100928.https://doi.org/10.1016/j.trgeo.2023.100928
14. Valsalan, P.; Baomar, T.A.B.; Baabood, A.H.O. IoT based health monitoring system. *J. Crit. Rev.* 2020, *7*, 739–743.
15. Yang, G.; Xie, L.; Mäntysalo, M.; Zhou, X.; Pang, Z.; Da Xu, L.; Kao-Walter, S.; Chen, Q.; Zheng, L.R. A health-IoT platform based on the integration of intelligent packaging, unobtrusive bio-sensor, and intelligent medicine box. *IEEE Trans. Ind. Inform.* 2014, *10*, 2180–2191.