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Health CNN-SMO: To Secure and Enhance the Medical Healthcare System by using Convolution Neural Network

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Abstract:- Now a day machine learning & deep learning and artificial intelligence has major important impact on the medical healthcare and pharma industry. Which useful for identifying, monitoring and treatment of the concern medical patients. By activating the diagnosis, individual therapies, this technical methodology is significantly improvising healthcare research methodology and outcome. An improvising trend in most famous culture and traditional healthcare involves remote monitoring of patient's health. Now a day most of the people are using advance smart devices like smart watches to track the fitness trackers, blood oxygen levels, heartbeat rate variability using different optimization and classification techniques. To collect and aggregates patients' health information or data from the different healthcare hospitals, healthcare-based research Centre, and healthcare smart devices users a fog computing and edge computing model that are going to implemented to enhance the early prediction of the deceases. To request and reply system series is provided by our research model to obtain and analyses medical based patients data remotely by the patient's doctors and physician.

***Keywords**:- Convolution Neural Network, Medical Healthcare, Machine Learning, Fog-Edge Computing.*

I. INTRODUCTION

Research in healthcare is being greatly improved by the enabling AI technology. These days, many use smart gadgets to keep an eye on their vital signs, such as blood oxygen levels, irregular heartbeats, and heart rate. This study develops a revolutionary medical healthcare system that uses various optimization and classification algorithms to analyses heart rate flexibility. Information from different users of cardiac care devices is compiled using a fog-based edge computing (EC) paradigm. Classifiers and optimization algorithms are used to assess the features taken from the dataset and make judgements. The classification procedure includes the tweaking of the model.

Traditionally, a thermometer is used to measure someone's temperature, a pulse monitor is used to measure heart rate, and a sphygmomanometer is used to measure blood pressure. However, with the advancement of technology, these parameters are now obtained via an electronic sensor device. As wearable Move ECG can measure an individual's heart's electrical movement, unlike smartwatches, it is now regarded as a sophisticated wearable healthcare technology. In order to identify accelerated heart rate, the Move ECG may measure walking distance, speed, elevation above the ground, running, swimming, and bicycling. The data can then be sent to the patient's cardiologist [1].

The Heart Guide, a wearable blood pressure monitor that tracks daily activity, walking distance, and calories expended, is a new health monitoring gadget. Another cutting-edge gadget is a self-adhesive wearable biosensor, which is a tiny patch-adhesive device that measures things like temperature and movement.

While technological progress provides a vast open platform for biological research and economic analysis, it also poses a barrier to emerging innovations in clinical care. A large amount of effort is principally included in smart healthcare, which aims to fulfil the growing potential for the best healthcare and overcome the shortcomings of traditional healthcare. It may be created as a variety of tools, programmers, facilities, and connections to conventional medical treatment. A wide range of clinical devices and software that link to medical care servers over the Internet form the basis of medical services in the Internet of Things (IoT) [1]. The addition of fog computing (FC) to cloud computing (CC) allows it to handle and retain large amounts of data generated by IoT devices [12].

The health care IoT has various benefits, including the ability to retain information and monitor a patient's physiological state from a distance. Unauthorized authentication and encryption procedures can expose IoT devices to dangerous risks, making them easily hackable [3]. Cardiovascular disease is the leading cause of mortality globally, and a major challenge in effectively forecasting this condition is the analysis of clinical data. Due to a number of minor underlying risk factors, including diabetes, hypertension, high cholesterol, irregular heartbeat, and frequent dissimilar variables, heart disease is an often difficult-to-diagnose coronary ailment [6].

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II. LITERATURE REVIEW

Shreshth Tuli *et al.*, [1] In this research article where author uses in proposed model that is the fog computing, deep learning and ensemble learning. Where it archives high accuracy in real life applications but not a user friendly because it takes data from files not directly from sensors.

Tiago M. Fernandez-Carames *et al.*, [2] Authors uses fog computing and blockchain technology where it is practically sufficient but automatically data reading is not possible.

Saurabh Shukla *et al.*, [3] Identification and authentication in healthcare internet-of-things using integrated fog computing based blockchain model, in this research article it used fog computing based blockchain architecture and advance signature-based encryption algorithms. The research outcome of this paper in medical applications reduces packet error and increases the accuracy of detecting malicious node but complexity of the system is high.

Integration of wearable technology, blockchain, and artificial intelligence for managing chronic diseases: a new paradigm in smart healthcare, Yi XIE et al., [5], uses blockchain technology, artificial intelligence, and archive AI based human monitoring is made reliable, but big data processing needs to be advanced.

Abhilash Pati *et al.*, [6], in this research article used different research methods that is machine learning, Deep neural network (DNN), Ensemble learning that archive privacy and security are good. But limitation of the research is very costly, and can analyses a single platform at a time.

III. PROPOSED METHODLOGY

After the Covid 19 the medical healthcare is one of the major concerns is to detect the health condition of the patient. First of all the arrhythmia based dataset that are collected form the Kaggle database. In the input dataset is an irregular that occurs when the electrical signal synchronizes the heart heats don't work systematically. The Fog-based edge computing (EC) model is implemented to gather data from different devices through data aggregation, where the collected data contain cardiac activity information about numerous heart care device users. The doctors can access details of the particular patient by generating a request/reply service provided by the system model. After obtaining the data of a particular patient, feature extraction is done on the data, in which features such as heart rate variability, statistical features, energy, entropy, and harmonic distress are been evaluated. This proposed based model uses CNN classifier in which the CNN has high performance on higher dimension data because of small model complexity and training difficulty. The execution of this methodology is implemented by using the python programming language and the performance metrics where accuracy of this model is high as compared to traditional existing model.

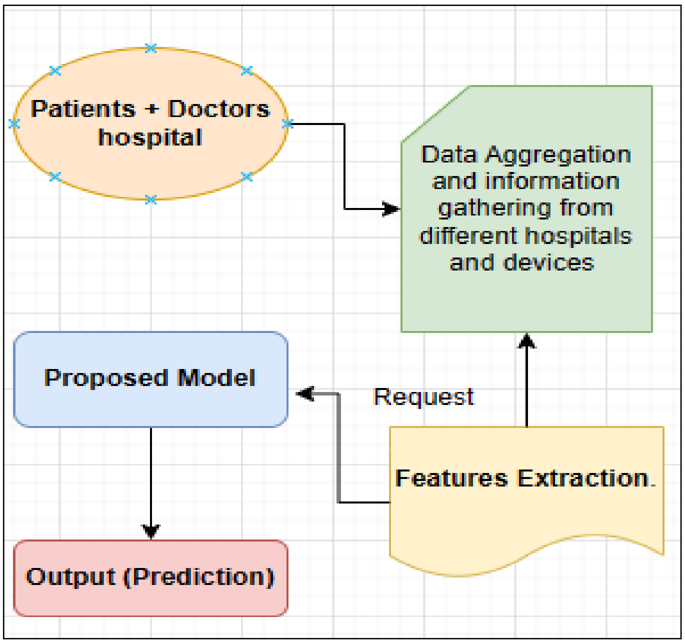

Fig 1: System Architecture of Proposed model.

IV. RESULT AND DISCUSSION

After gathering of the input data or information form the dataset then the next step is the preprocessing. for preprocess the data to load the datasets using NumPy, create new data list for appending the values, standardization of value, append sequences and labels to the respective list.

```
global fs
records = np.loadtxt( fname: "mit-bih-arrhythmia-database/RECORDS", dtype=int)  # read a file
all_sequences, all_labels, subject_map = [], [], []                # empty lists
window_sec = 3
for subject in records:
    record = wfdb.rdrecord(f'mit-bih-arrhythmia-database/{subject}')
    annotation = wfdb.rdann(f'mit-bih-arrhythmia-database/{subject}', 'atr')
    atr_symbol = annotation.symbol
    atr_sample = annotation.sample
    fs = record.fs              # Sampling frequency
    scaler = StandardScaler()   # Standardization
    X = scaler.fit_transform(record.p_signal)
    subject_labels = []
    for i, i_sample in enumerate(atr_sample):
        label = classify_beat1(atr_symbol[i])
        sequence = get_sequence(X, i_sample, window_sec, fs)
        if label is not None and sequence.size > 0:
            all_sequences.append(sequence)                # append sequences and labels
            subject_labels.append(label)

    normal_percentage = sum(subject_labels) / len(subject_labels)        # Percentage
    subject_map.append({
        "subject": subject,
        "percentage": normal_percentage,
        "num_seq": len(subject_labels),
        "start": len(all_labels),
        "end": len(all_labels) + len(subject_labels)
```

➢ *Important Features for Extraction*
- Heart Rate Variability features time domain, frequency domain
- Statistical features
- Harmonic distress
- Entropy features
- Energy features

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- *Features are Extracted from above Mentioned Terms and Stacked Together.*

```
1 usage
def Main_feature_extraction(data):  # Feature Extraction function
    hrv = time_domain(data)
    hrv_1 = frequency_domain(data)
    statistical_feat = statistical_feature(data)
    harmonic_feat = harmonic_distress(data)
    harmonic_feat = np.asarray(harmonic_feat)
    entropy_feat = entropy_features(data)
    energy_feat = energy_features(data)

    hrv = hrv.flatten()  # converting 2d arrays into 1d arrays
    hrv_1 = hrv_1.flatten()
    statistical_feat = statistical_feat.flatten()

    feat = np.hstack((hrv, hrv_1, statistical_feat, harmonic_feat, entropy_feat, energy_feat))
    return feat
```

- *Performance Analysis of Accuracy*

1)	40 (2)	50 (3)	60 (4)	70 (5)	80 (6)
	40	50	60	70	80
RO based CENN with Epochs=20	89.62325899773171	90.70224583999955	93.65139183169818	94.50251374390332	96.5144910254593
RO based CENN with Epochs=40	89.62480106792998	90.7022517406945	93.65165843402062	94.50866664203883	96.5246773844974
RO based CENN with Epochs=60	89.63073079362864	90.70225487178934	93.65358489088094	94.50939994796597	96.5837566551274
RO based CENN with Epochs=80	89.63797469571753	90.70232528645465	93.65532184862533	94.51739790148686	96.6339686218566
RO based CENN with Epochs=100	89.71787152002659	90.70234917832953	93.65634861675553	94.51857082031201	96.7135028517805

V. CONCLUSION

The healthcare is the humanity-based service to save the humanity. In this research the proposed model secures the heart care system of heart disease using the convolution neural network based on the deep learning technology. This model gives high performance accuracy that is 96.71% as compared to traditional existing model.

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