Resolving Data Overload and Latency Issues in Multivariate Time-Series IoMT Data for Mental Health Monitoring

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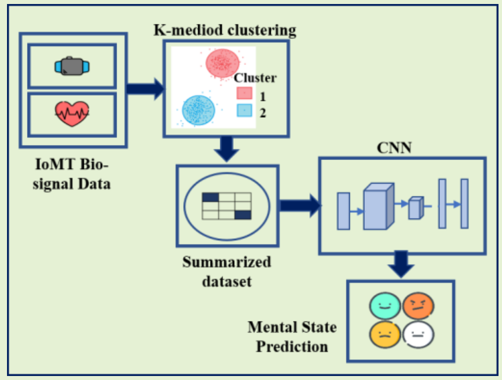
Abstract— **Pervasive healthcare services have evolved substantially in the recent years with IoMT rapidly changing the pace and scale of healthcare delivery. A promising application of IoMT is to fetch patterns of mental behaviour symptomatology based on bio-signals and transfer it to the corresponding hospital or psychologist for remote monitoring. But the data volume & performance, device diversity & interoperability, hacking & unauthorized use and acceptance & adoption barriers still restrain the practical and competent use of these devices. This research presents a plausible solution to surmount the data overload and processing latency in real-time sensory data collected through wearable devices for mental health monitoring. We propose a modified k-medoid data clustering technique based on time-frame restricted intra-cluster similarity calculations to obtain a summarized version of the original benchmark WESAD dataset for which the degree of information lost is minimum. A CNN is then trained on this summarized dataset for classification of mental state into the baseline, stress and amusement categories. The results show a significant reduction in the average execution time by 34% with a comparable accuracy to the original dataset, thus offering prompt real-time healthcare analytics.**



Index Terms— **Clustering, CNN, IoMT, k-medoids, Mental State**

I. Introduction

ARTIFICAL intelligence (AI), Internet of Medical Things (IoMT) and big data analytics have revitalized the healthcare industry with an evident paradigm shift from the *'reactive healthcare'* to the *'proactive patient care'*. The applications range from the rudimentary chronic morbid disease management (diabetes, asthma, heart disease, etc.) to remote-assisted living (tele-health), wellness and preventive care (lifestyle assessment), remote intervention and improved drug management. Patients use medical devices, monitoring tools, wearables, and other sensors collectively referred to as the IoMT, that can transmit signals to other devices via the internet and cloud services [1, 2]. It is imperative to synthesize, process, analyze, visualize and integrate this massive amount of sensory data to generate value and insights for chronic disease management and patient care needs. Typically, the acquired data is transmitted over the network to the cloud for storage & analytics. This data received in near real-time allows doctors and caregivers to monitor an array of vitals, dynamically manage treatment plans, and conduct a consult or intervention over a webcam. Further, the data supports predictive analytics, allowing doctors to increase their accuracy of diagnoses by detecting emerging health patterns much faster. Thus, by leveraging the data that IoMT devices collect, AI is proving useful in enabling real-time remote measurement, analysis of patient data, enhancing effectiveness of care and decreasing the overall costs [3]. A promising application of IoMT is to fetch patterns of mental behaviour symptomatology based on bio-signals and transfer it to the corresponding hospital or psychologist for remote monitoring [4, 5]. The primary use of AI in mental healthcare includes:

- Early detection, flagging risks, and prediction
- AI-based chatbots to help patients 24/7

Mental health monitoring is more challenging than the physical health monitoring because firstly, human psychology varies dynamically; secondly, it is difficult to fetch the patterns of mental behavior; thirdly, behavioural symptomatology of mental illness may be visible at a later stage and lastly people with disturbed mental health are constantly in denial of the illness and have associated fears of cultural and social stigma. The use of smart algorithms for IoMT data analytics may provide psychiatrists and therapists with valuable insights which may help faster diagnosis and targeted treatment plans for mental well-being [6, 7].

According to a recent report by Deloitte, the IoMT market is expected to be worth \$158.1 billion by 2022 [8], but a few key challenges are standing in the way of its continued growth. These include the network-driven, data-driven,

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device-driven and user-drives issues as given in fig.1.

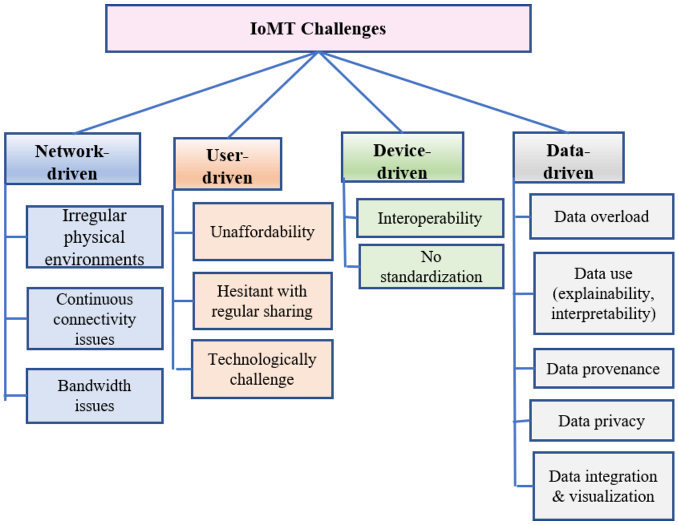

Fig.1. Challenges in IoMT adoption

- *Network-driven issues:* The large volume of data transmitted can strain the network resulting in bottlenecks [9]. Healthcare applications can't tolerate latency and require significant bandwidth for ingesting data. While integrating IoT into the healthcare industry, it is mandatory that the devices be movable and with a guaranteed continuous connectivity. But this is interrupted due to the irregular physical environments.
- *Data-driven issues:* IoMT devices record tons of data and utilize it to gain vital insights. However, the volume of data is so colossal that gaining insights from it is turning out very challenging for practitioners and ultimately affects the efficacy of decision-making. Moreover, this concern is rising as more devices are connected which record more and more data making data overload a primary issue. Also, while AI technologies are extraordinarily powerful, adoption of these algorithms in healthcare has been slow because doctors and regulators cannot verify the results making data use, data provenance, interpretability and explainability a rising concern. Further, healthcare data may contain sensitive attribute values which may lead to identify disclosure. Ensuring informational privacy (secrecy, confidentiality, data protection, or anonymity) of healthcare data is imperative for ensuring quality of care, enhanced autonomy, and preventing economic harm, embarrassment, and discrimination [10]. Lastly, although there are vast amounts of data in the healthcare sector, this data is often very fragmented and dispersed. By collecting information through sensors, integrating such information on a single platform, and visually presenting it through a smart healthcare command centre, healthcare staff can quickly acquire meaningful information that enables them to improve the quality and efficiency of healthcare services. Thus, data overload, lack of explainability, privacy, data integration & visualization are the key data-driven concerns.
- *Device-driven issues:* Data formats and communication protocols may be different for larger devices. This can significantly increase the time it takes for these devices to integrate with existing IoMT devices. Lack of standardization in terms of definitions of devices, data format and communication protocols affects data interchange and interoperability impeding the expediency and effectiveness of IoMT [2].
- *User-driven issues:* Unaffordability is one of the key user concerns where the cost of IoMT is higher for patients. Another major concern is that the patients may not be comfortable with regular sharing of their health information or may be technologically challenged.

At its core, the IoMT are equipped with state-of-the- art sensors that have the ability to record and transfer vital healthcare data thus enhancing the competence of healthcare delivery and ensuring improved patient outcomes [11]. But quite clearly, the data management systems must cater to the phenomenal volume, variety and velocity of data which may need huge storage and make analytical, process and retrieval operations cumbersome and time-consuming. Though the recent advancements in 5G wireless technology and edge computing enable connected devices to process data closer to where it is created, it may partially improve the response time [12]. Still the overwhelming amount of data can create havoc and the healthcare practitioners might miss on some important information. To resolve this problem, a plausible solution is to condense/ summarize the dataset such that it's still an informative version of the entire dataset [13]. This research uses the k-medoid clustering [14, 15] to obtain the condensed version of the original dataset for which the degree of information lost is minimum and then trains a convolution neural network (CNN) on the summarized data set for diagnostic classification. This would help resolve the data overload issue. Though k-medoid suffers from scalability issues, the intra-cluster similarity calculations have been restricted using a time-frame window mitigating the computational cost. The condensed data eventually decreases the processing latency and delivers prompt real-time analytics.

We consider the publicly available WESAD (Wearable Stress and Affect Detection) dataset [16], which contains bio-signal data of 15 subjects measured through two IoMT devices, namely RespiBAN and Empatica E4 for a period of 2 hours. The multivariate time-series data consists of 12 bio-signals: electrocardiogram (ECG), electromyogram (EMG), body temperature (TEMP), respiration (RESP), blood volume pressure (BVP), electrodermal activity (EDA) and three axis acceleration (ACC). ECG, EDA, and EMG are analog time-series data and to analyze continuous time-series data it is fragmented into finite intervals. For example, to identify the mental state of an individual, the time-series data in the benchmark WESAD dataset is broken at an interval of 1 second with the sliding window of 0.25 seconds, as the effect of a stimulus can occur over a short interval of 2 seconds. The conversion of analog data to discrete values makes a total of 63000000 instances just for a period of 2 hours in this dataset.

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This huge amount of data is not easy to analyze for any medical practitioner even for a few patients on a daily basis. By using k-medoid cluster analysis, summary can be generated as it partitions n-observations into k-clusters in which each observation belongs to the cluster with the closest medoid. The original WESAD data is initially transformed by converting the analog bio-signals into discrete values and further into numeric values. Clustering is then used to generate the centroid for each cluster and these centroids now characterize the summarized WESAD dataset. Finally, CNN is trained using this summarized WESAD data containing k-medoids, to predict the mental state of an individual into three categories as stress, amusement or baseline. Thus, the primary contributions of this research are:

i. A solution to surmount data overload and processing latency in real-time sensory data for mental health monitoring.
ii. To assess the efficiency of a deep learning model trained using the summarized version for mental state prediction.

Learning algorithms offer unprecedented insights into diagnostics, care processes, treatment variability, and patient outcomes [17, 18]. Pertinent studies to resolve various IoMT issues are available. Fadlullah et al. [19] identified that network and computational congestion problems may impact the real-time analytics of the healthcare data and proposed a deep learning based IoT edge analytics approach to support intelligent healthcare for residential users. Chen et al. [20] proffered a cognitive computation based smart healthcare system on the edge to resolve the multimodality, latency and resource issues. In 2020, Alfarraj and Tolba [21] introduced a responsive model for effectively handling IoMT data regardless of the time factor. In 2021, Goswami et al. [22] proposed a method for efficient power utilization for remote health monitoring.

Recent studies on mental health monitoring using WESAD dataset have reported the use of various machine learning and deep learning algorithms [23-26]. In 2021, Sharma et al. [27] proposed a model for computational intelligence on the edge. The authors reportedly summarized the dataset using an optimized fuzzy C-means clustering algorithm to finally train a deep hierarchical model for affective state detection in the WESAD data.

The next section outlines the details of the proposed model followed by the results and discussion in section 3. Finally, the conclusion and future work is given in the last section.

II. The Proposed Model for Fast Predictive Analytics

A CNN based deep learning model is put forward which facilitates predictive analytics of mental health to detect and monitor disturbed mental states. The model is trained using a summarized [26] version of the original IoMT dataset created using cluster analysis, which directly curbs the data overload issue and simultaneously reduces the processing time and consequent decision latency. Fig.2 depicts the architecture of the proposed model.

The proposed fast analytical model for detecting the mental state of an individual consists of the following two architectural components:

- K-medoid clustering technique for summarized dataset
- CNN trained using summarized dataset to detect the mental state

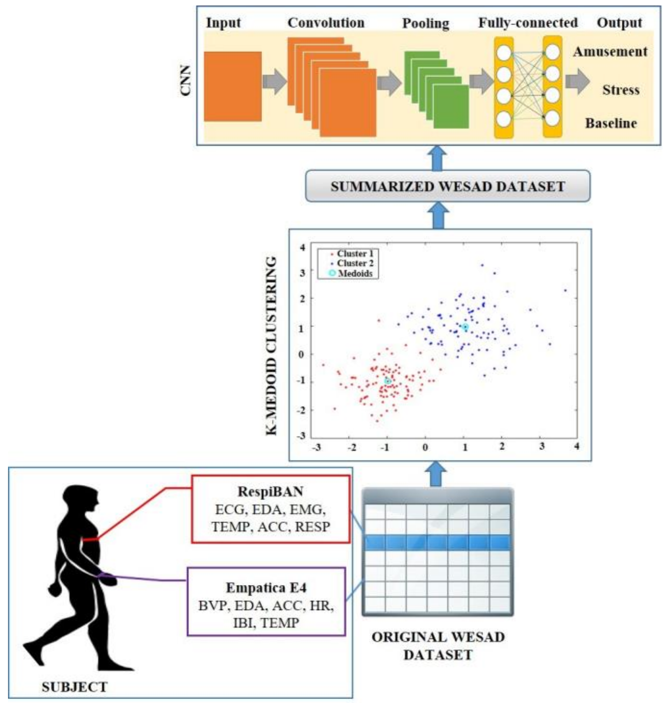

Fig.2. Architecture of proposed model

Clustering is counted amongst the key unsupervised learning techniques. Clustering of multivariate time-series data is specifically useful in exploratory data analysis and summary generation as it groups objects into several clusters by measuring the similarity between objects through distance and identifies the characteristics of each cluster [28]. Typically categorized as partition-based, density-based, grid-based hierarchical and model-based clustering techniques [29], each of these has its pros and cons while being used for clustering of time-series data. Though hierarchical clustering is a strong contender owing to its visualization capabilities and with no prerequisite of cluster initialization, it suffers due to its quadratic complexity and lack in scalability. Alternatively, the partition-based clustering techniques such as k-means and k-medoids (partitioning around medoid, PAM) are faster.

In this research, we use the k-medoids cluster analysis for data reduction. The 'K-Medoids Clustering' combines the k-Means and the medoid shift algorithms aiming to partition n-observations into k clusters in which each observation belongs to the cluster with the closest medoid. That is, instead of taking the mean value of the object in a cluster as a reference point, medoids can be used, which is the most centrally located object in a cluster. The medoid of a finite data set is a data point (one of the observations) from this set, whose average dissimilarity to all data points is minimal. It offers an improvement on the k-means clustering, in terms of execution time and non- sensitivity to outliers or noise. It is effective as it does not depend on the order in which data points are

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examined. Moreover, the cluster center is part of the dataset, unlike k-means where the cluster center is gravity based.

Algorithm 1: K-medoid

Input: WESAD dataset-D, number of clusters-k
Output: Medoids M
1: Arbitrary choose k object as initial medoids
2: Assign each remaining object to nearest medoids
3: Calculate objective function: *the sum of dissimilarities of all objects to their nearest medoid*
4: Randomly select a non-medoid object, O_{ramdom}
5: If objective function improved.
6: Swapping O and O_{ramdom}
7: Compute Total Cost of swapping
8: Repeat (3-7) Until no change

The second component of the proposed model uses a CNN to predict the mental state of an individual into three categories, namely stress, amusement and baseline for real-time monitoring. CNN is a neural network with a sequence of convolutional layers (often with a pooling step) and then followed by one or more fully connected layers. A convolutional layer has a number of filters that does convolutional operation [31]. CNN is faster to train as convolutions can be done in parallel, thus utilizing full advantage of GPU parallelism. The functionalities of each layer in CNN is as follows:

- *Convolution layer:* computes the output of neurons that are connected to local regions in the input, each computing a dot product between their weights and a small region they are connected to in the input volume. The convolution layer's parameters consist of a set of learnable filters
- *RELU layer:* applies an element-wise activation function, such as the max (0, x) thresholding at zero. This leaves the size of the volume unchanged.
- *Pooling layer:* performs a down sampling operation along the spatial dimensions (width, height). Its function is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network. The pooling layer often uses the Max operation to down-sample the previous layers feature map.
- *Fully-connected (FC) layer:* Fully connected layers are the normal flat feed-forward neural network layers and may have a non-linear activation function or a Softmax activation in order to predict classes. The FC layer basically computes the class scores, resulting in volume of size [1x1xN], where each of the N numbers correspond to a class score, such as among the N categories.

Both the clustering operation and the predictive model have been trained on a system with a 2.7 GHz Intel core i5 processor with 16GB RAM over the WESAD dataset. The WESAD data was collected by Schmidt et al. in 2018 [16] at the University of Siegen, Germany for analysing the affective state of 17 individuals by monitoring their physiological changes through various biomarkers collected through Empatica E4 (wrist-worn) and RespiBAN (chest-worn) devices in a controlled lab environment for a period of 2 hours. The final data for only 15 subjects was made publically available with entries of 2 subjects considered as invalid. WESAD tracks the bio-signals like ECG, EDA, and EMG for determining the stress levels which are analog signals and for training a deep learning model this time-series analog data is discretized by breaking the data at finite intervals. Each subject after discretization has 40 lakh instances approximately, as the time-series data is broken into a finite interval of 1 second with 0.25 second as the sliding window to monitor the change [32].

In general, clustering is used to identify different types of instances available, i.e. to categorize the instances using unsupervised learning techniques. Clustering groups the entities of similar nature together, but in time-series data especially in healthcare, even with similar instances, data cannot be grouped together, as the context in terms of pre and post condition have an effect on the data. Therefore, to resolve this constraint the K-medoid clustering algorithm has been modified to accomplish the cluster generation for a particular time frame only. In a basic K-medoid clustering algorithm, K data points are chosen at the beginning, and then clusters are formed by analyzing the similarity with rest of the data with these k- medoids and after calculating the similarity with each medoid, the point is assigned to the nearest medoid. Once all the data has been categorized into k-partitions, the medoid (centralized) point of each partition is varied from the same partition iteratively until all the points have been chosen once as the medoid point, and then the optimized clusters are provided as the output. There are two issues with this basic approach:

- In each iteration, the similarity is calculated again with each instance in the dataset, for large datasets like WESAD, calculating similarity with 40 lakh entries for a single subject in each iteration is a tedious and time-consuming task.
- A person can have identical bio-signals at different time instance, for example, a person sitting on a chair is in baseline state, on receiving a work assignment, and while performing the task his physiological state changes, but once the task is over and the person relaxes again, he again goes into the baseline state, that is the person has identical bio-signals pre and post the task. In basic k-medoid clustering technique, the states pre and post the task will be put under the same cluster based on their similarity without taking the time-constraint into account.

Therefore, the modified K-medoid clustering algorithm has been used, in which rather than calculating the similarity function with all the data points, in each iteration, the similarity of the medoid is calculated with only 80 data points before the medoid and 80 points after the medoid in the continuous data, ensuring that no two-time varied instances should be clubbed together. Thus, to resolve the data overload issue in real-time IoMT data processing, we reduce the size of the data by performing clustering on this time-series data and the centroid of a cluster is used for analysis rather than every instance of the cluster.

As per the observation made by Siirtola in 2019 [23], the 'affect' perceived depends upon the time window taken. The use of these time segments (windows) capture more discriminative information for the same input signal. Affective states are typically short and need a time window of seconds.

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But analysing every single second of data may not be effective and therefore we consider the window size of 3 seconds to detect any physiological change in the body and maintain the uniformity of our experiment. The base hypothesis for identifying the optimal clusters for data reduction is empirically analysed for performance accuracy using varying time window. Based on this analysis, to initialize the model, 2400 clusters for WESAD (2 hours => 7200 seconds) are used, and 200 extra cluster points are chosen for any outlier or frequent change in the body. As in real-time analysis the clustering process will be performed for streaming data, waiting for upcoming data can be ruinous in certain scenarios and therefore the optimized segment of 3 second was chosen for time coherence. This 3 second time segment cannot be generalized for every health condition prediction model.

III. Results & Discussion

Various bio-signals measure different physiological changes in the body and each indicates some sort of psychological or emotional affect a person is experiencing. That is, to understand the current mental state of a person each bio-signal plays an important role. The bio-signals in the WESAD dataset are:

- *RespiBAN:* Electrocardiogram (ECG), Electromyogram (EMG), Body Temperature (TEMP), Respiration (RESP), Blood Volume Pressure (BVP), Electrodermal Activity (EDA), Three Axis Acceleration (ACC)
- *Empatica E4:* Body Temperature (TEMP), Blood Volume Pressure (BVP), Electrodermal Activity (EDA), Three Axis Acceleration (ACC)

As observed from the work carried by different researchers on WESAD, each person acts differently even under similar circumstances and their bodies show different physiological changes for stress, amusement, depression and for neutral state. Therefore, the model should be accustomed as per the individual. To train the model for each individual, the prediction model was implemented separately on each individual. Each individual has around 40, 00000 instances for two hours with 12 different bio-signals. The data was initially summarized by clustering using the modified K-medoid approach and after generating the clusters, the mediod point of each cluster was chosen as a representative for each cluster. In K-medoid the number of clusters and the initial medoid point of the cluster has to be provided. In execution, k was provided as 2600, first medoid was initialized with the 80th instance, afterwards every 120th instance was chosen as the next medoid point. During execution, the similarity of each medoid point was calculated only with 80 before instances and 80 post instances, a total of 200 iterations were performed, by setting the terminating condition, to avoid falling in the local optima. Table 1 and table 2 depict the original WESAD and the summarized WESAD data of subject 5.

The reduced dataset was then split into a 70:30 ratio for training and testing the deep-learning model, with 4-cross fold validation. Each subject was trained and tested individually, before and after summarizing the data. To analyze the effectiveness of the proposed model, the model is evaluated using accuracy and execution time, to understand the reduction in decision-latency time. Fig.3 and Fig.4 show the comparison of pre- and post-summarization on predicting the mental state of a person using CNN in terms of accuracy and execution time (in seconds) respectively.

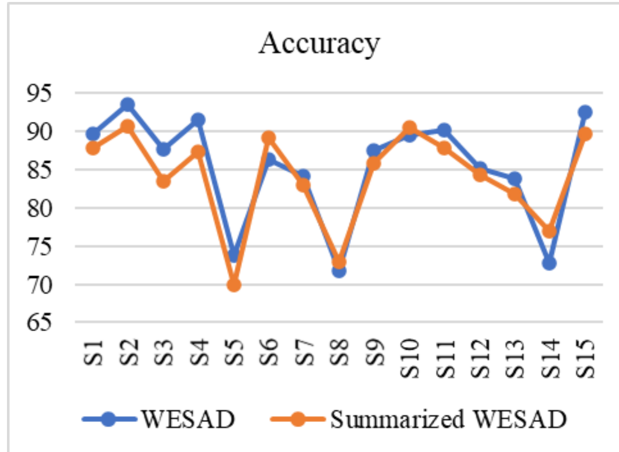

Fig. 3. Model accuracy using original and summarized WESAD

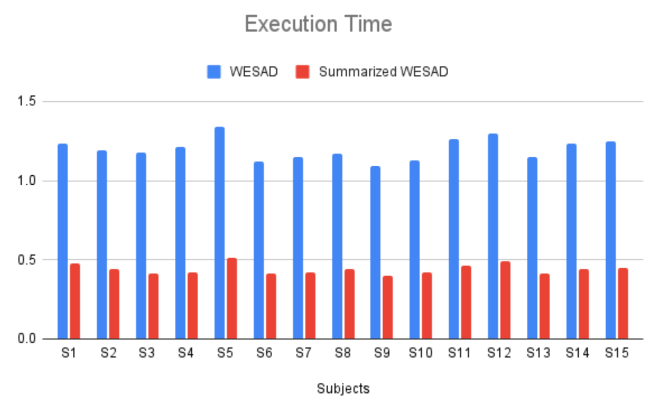

Fig. 4. Model accuracy using original and summarized WESAD

To handle the data overload issue and to fasten the processing time, the features (bio-signals) can also be reduced. As experimented by Schmidt et al. in 2018 [16] & Siirtola in 2019 [23], by clubbing different bio-signals for WESAD it was observed that a subset of bio-signals can predict the mental state with close accuracy as to considering all the bio-signals. To test the hypothesis, rather than sub-selecting the bio-signals to predict the mental state on WESAD data, we experimented by taking the bio-signals from each device individually. 4 bio-signals measured by both the devices are common and training a deep neural network on the identical result generated by two different devices is a waste of the processing power and increases the computational power.

Fig. 5 and fig. 6 shows the accuracy and execution time of the model on complete WESAD data, on only Empatica E4 data of each subject, and on only RespiBAN data of each subject respectively. It was observed that Empatica E4 has predicted the state better in comparison to RespiBAN with 81.77 and 80.57 accuracy respectively, but both have performed poorly in comparison to complete WESAD data which resulted in 85.37 accuracy.

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TABLE 1.
ORIGINAL WESAD DATA OF SUBJECT 5

	Empatica E4								RespiBAN							
Time	BVP	EDA	ACC-A	ACC-B	ACC-C	HR	IBI	TEMP	ECG	EDA	EMG	TEMP	ACC-X	ACC-Y	ACC-Z	RESP
0	0	0	0	5	63	60	0.85941	27.61	31600	9942	32567	26.533	37303	32479	31367	34015
0	0	0.40031	0	5	63	60.5	0.85941	27.61	31636	9923	32739	26.542	37291	32495	31377	34015
1	0	0.47577	0	5	63	60	0.85941	27.61	31709	9954	32850	26.551	37287	32497	31364	34015
1	0	0.486	0	5	63	59.75	0.96879	27.61	31763	9925	32672	26.549	37279	32487	31342	34025
1	0	0.48856	0	5	63	59.8	0.96879	27.59	31810	9955	32867	26.539	37273	32489	31373	34049
2	0	0.48984	-1	5	63	60.67	0.90629	27.59	31881	9971	32661	26.534	37282	32485	31367	34039
2	0	0.48984	-1	5	63	61.43	0.95317	27.59	31982	9927	32693	26.555	37269	32488	31365	34036
2	0	0.48856	0	5	63	62.12	0.85941	27.59	32140	9955	32783	26.565	37271	32487	31356	34039
3	0	0.486	0	5	63	62.67	0.75003	27.59	32267	9929	32828	26.578	37268	32490	31357	34055
3	0	0.48344	0	5	63	63.1	0.84379	27.59	32415	9937	32553	26.549	37267	32491	31355	33822
3	0	0.48856	0	5	63	63.45	0.82816	27.59	32439	10005	32757	26.549	37277	32485	31340	34049
4	0.01	0.48984	0	5	63	63.75	0.76566	27.59	32401	9939	32788	26.539	37292	32475	31335	34069

TABLE 2.
SUMMARIZED ORIGINAL WESAD DATA OF SUBJECT 5

		Empatica E4								RespiBAN							
Cluster	Time	BVP	EDA	ACC-A	ACC-B	ACC-C	HR	IBI	TEMP	ECG	EDA	EMG	TEMP	ACC-X	ACC-Y	ACC-Z	RESP
C1	1	0	0.39	-0.167	5	63	60.1	0.90369	27.6	31733	9945	32726	26.541	37286	32489	31365	34026
C2	4	0.002	0.488	-0.167	5	63	62.8	0.83337	27.59	32274	9949	32734	26.556	37274	32486	31351	34012
C3	7	-0.02	0.491	-0.667	4.8333	62.833	64.8	0.83077	27.57	31955	9942	32775	26.561	37279	32478	31343	34049
C4	10	0.875	0.49	0.1667	5.5	62.833	65.4	0.90629	27.57	32053	9959	32725	26.549	37270	32485	31357	34021

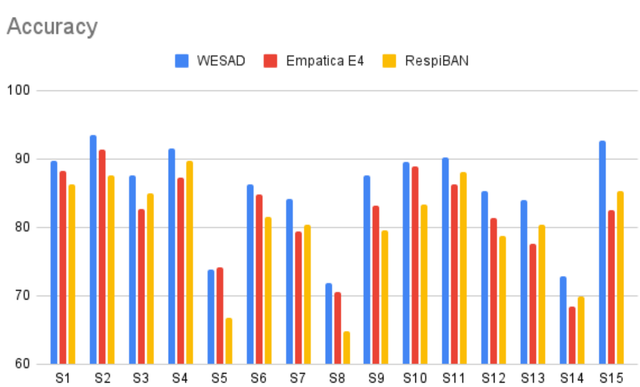

Fig. 5. Accuracy using WESAD vs. individual wearable data

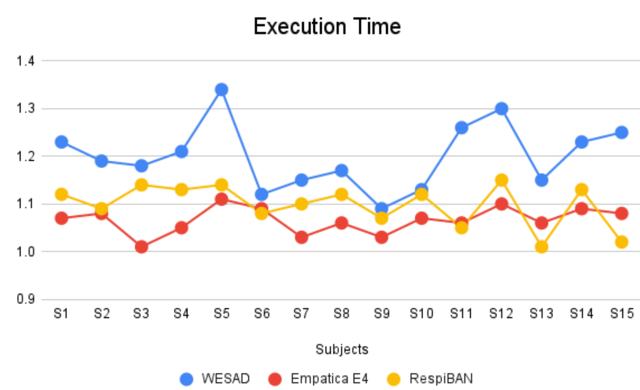

Fig. 6. Execution time using WESAD vs. individual wearable data

Although, the model can perform better by choosing a subset of combined features of the two devices. To evaluate the efficiency of the proposed data reduction strategy, the improved k-medoid clustering algorithm has been used and evaluated on Empatica E4 and RespiBAN data separately too. Table 3, summarizes the accuracy and execution time for all the 3 datasets for pre- and post- summarization.

Fig. 7 and fig. 8 represents graphically the comparison of accuracy and execution time for all the scenarios, that is, original WESAD, summarized WESAD, Empatica E4, summarized Empatica E4, RespiBAN and summarized RespiBAN.

TABLE 3.
SUBJECT-WISE ACCURACY AND EXECUTION TIME

Subjects	WESAD		Summarized WESAD		Empatica E4		Summarized Empatica E4		RespiBAN		Summarized RespiBAN	
	Accuracy	Time	Accuracy	Time	Accuracy	Time	Accuracy	Time	Accuracy	Time	Accuracy	Time
S1	89.71	1.23	87.94	0.48	88.19	1.07	87.21	0.39	86.31	1.12	84.97	0.38
S2	93.54	1.19	90.71	0.44	91.37	1.08	90.29	0.36	87.59	1.09	85.49	0.34
S3	87.67	1.18	83.54	0.41	82.68	1.01	83.21	0.33	84.96	1.14	81.65	0.38
S4	91.49	1.21	87.39	0.42	87.19	1.05	83.47	0.35	89.73	1.13	88.71	0.36
S5	73.87	1.34	69.89	0.51	74.21	1.11	69.34	0.38	66.81	1.14	65.32	0.39

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S6	86.35	1.12	89.13	0.41	84.73	1.09	85.92	0.35	81.59	1.08	79.08	0.34
S7	84.19	1.15	83.02	0.42	79.38	1.03	76.75	0.38	80.36	1.1	78.41	0.35
S8	71.83	1.17	72.91	0.44	70.64	1.06	68.78	0.32	64.81	1.12	62.84	0.37
S9	87.56	1.09	85.83	0.4	83.15	1.03	79.95	0.35	79.62	1.07	80.03	0.36
S10	89.49	1.13	90.56	0.42	88.91	1.07	87.27	0.38	83.37	1.12	82.78	0.35
S11	90.28	1.26	87.91	0.46	86.27	1.06	84.89	0.37	88.06	1.05	87.46	0.31
S12	85.24	1.3	84.28	0.49	81.34	1.1	81.08	0.4	78.81	1.15	78.07	0.38
S13	83.91	1.15	81.84	0.41	77.63	1.06	76.92	0.39	80.45	1.01	76.7	0.34
S14	72.77	1.23	76.91	0.44	68.46	1.09	65.87	0.41	69.98	1.13	67.16	0.37
S15	92.62	1.25	89.79	0.45	82.53	1.08	80.79	0.39	85.23	1.02	84.23	0.34
Average	85.36	1.2	84.11	0.44	81.77	1.06	80.11	0.37	80.51	1.09	78.86	0.35

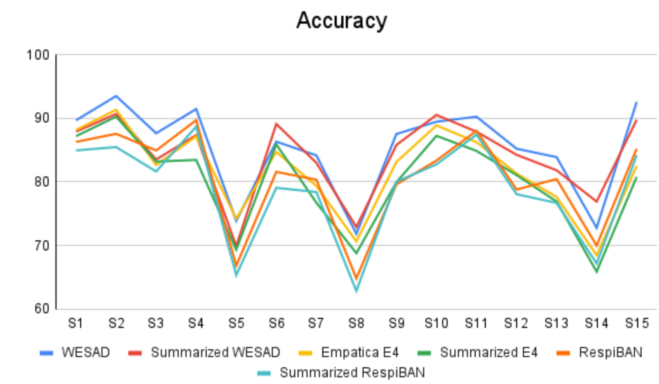

Fig. 7. Accuracy comparison for all scenarios

Fig. 8. Execution time comparison for all scenarios

As evident from the results, the summarization technique used has reduced the average execution time by 34%, whereas the accuracy has declined only by 0.98% for all the three scenarios. In real-time healthcare, this can reduce the decision latency time for critical medical services and provide an accurate detection of the current mental health condition of an individual. As a solution to mitigate the risk associated with the minor reduction in accuracy, the model can be trained using original (non-summarized) data and while analyzing the health condition in real-time to avoid the latency in decision making, the k-medoid clustering can be used for summarizing the continuous incoming data. Also, as the model is currently trained on only 2 hours of bio-signals data, to achieve better accuracy data can be collected for a longer period of time. Further, as smart healthcare services in real-time need high precision, as inefficiency can result in a loss of life, therefore, to increase the effectiveness/accuracy of prediction of health analysis in real-time, each feature can be trained explicitly with computationally less expensive and well-learned models.

IV. Conclusion

This work substantiates that integrating stakeholders within the pervasive healthcare paradigm which include practitioners, patients, processes, and connected medical devices along with the use of disruptive technologies like AI, blockchain, and robotics can improve the diagnostic methods and increase the quality of patient care. Although IoMT devices facilitate disease prevention, fitness promotion, and remote intervention in emergency situations, the overwhelming amount of data make timelines and decision-making difficult for medical experts. In this research, a CNN model was trained using a summarized version of the original IoMT based mental health WESAD dataset. We used the k-medoid technique for cluster analysis to create the summarized version of the WESAD dataset, but as k-medoid suffers from scalability issues we restricted the intra-cluster similarity calculations using a time-frame window and mitigated the computational cost. Evidently the data clustering technique reduced the average execution time.

As possible future direction, we intend to work on other data-driven issues pertaining to IoMT, especially as the devices and data are highly vulnerable to cybersecurity risks. Moreover, healthcare diagnostic models are critical for human life and need proper justification and 'context' to the diagnosis. Explainable AI can be used for data interpretability and improving human understanding, for determining the justifiability of the decision made by the machine, introducing trust and reducing bias in healthcare decision making.

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