Multi-Modal Social Networks with IoT-Enabled Wearable Devices for Healthcare

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Abstract. The combination of wearable devices and social networking sites has led to personalized health clinics. Since people are connected, their health is also interconnected. The COVID-19 pandemic has shown how important it is to use social media and wearable devices to track, listen to, interact with, and share important health information. These techniques improve healthcare by measuring the user's activity, stress, blood pressure, body temperature, etc. This research proposes a framework to develop a standardized system using wearable devices and social media platforms for healthcare that will focus on detecting and monitoring chronic diseases like BP, diabetes, mental health, etc. The proposed framework works efficiently on two different interrelated datasets with appreciable accuracy.

Keywords: Social Networking, Wearable Devices, Healthcare, Chronic disease, Generalization, Convolution, and Sequential Neural Networks

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1 Introduction

Independent exchanges between social networks and the Internet of Things (IoT) [22] are a growing interdisciplinary field that uses today's promising Social Internet of Things perspectives. People are forming their communities around health conditions using online social networks. Together, online social networks [19, 21] and wearable devices play a significant role in collecting and sharing information about patients worldwide, making it easier to keep track of their health. However, using the data made by wearable devices and social networks together is problematic because it generates gigantic amounts of continuous, unstructured, multimodal data. Our healthcare monitoring system has trouble using this helpful information from social networks and sensor data [23, 11]. With old machine learning methods and architecture, it is impossible to process large amounts of unstructured, multimodal data accurately [3, 12]. Therefore, a novel framework for a healthcare monitoring system needs to be based on the fusion of social networks and wearable devices that improve accuracy and have good efficiency [1].

Social relationships have powerful effects on mental and physical health. Being excluded from the community meant a death sentence; our brains are still hardwired for social interactions. Medical care can be done at home with wearable devices, and this information can be shared worldwide through social media so that people can get ideas or be inspired. If you seek an efficient way to analyze social media information, nothing can beat the IoT experience. When IoT devices are connected to social media tools, they form the Social Internet of Things (SIoT). Combining these technologies into an interactive healthcare environment is needed immediately to improve the safety and quality of care and the efficiency of medical staff by giving them access to helpful healthcare information. In the new social media era, monitoring tools will work with billions of IoT devices that can connect to social networks. Modern technologies like smartphones, smart wristbands, social media, m-Health, and mobile apps are being used more often in the medical field due to features like low cost, usability, portability, many users, and initial reliability.

Companionship sometimes exhibits a stronger association with psychological health than support. People use social media, IoT every day, whether they know it or not. Healthcare professionals use social networks professionally, exploiting all their capabilities enormously; expert questions, recommendations, learning, discussion, aggregating patient cases, etc. Hence, in this article, we have proposed a novel framework with the association of social networks and wearable medical devices to standardize the healthcare systems for detecting and monitoring chronic diseases. We have considered depression and ECG datasets for our experiment. These two datasets are interconnected as an ST depression is a specific outcome that may appear in a person's ECG results. It happens when a person's ST segment looks abnormally low and is below the baseline. The proposed novel framework is capable of dealing with single modalities as well as multi-modalities. Our experiment results show that the proposed model works well with reasonable computational resources. We summarize the main contributions of our work as follows:

- We explore and propose a novel multi-modal framework using Social Networks, Internet of Things, Machine Learning, and Big Data for monitoring chronic diseases which generate an early warning, and
- We add the state-of-art multimodal knowledge fusion techniques for effective utilization of the system in healthcare.

2 Related Work

Users of social media have both positive and negative experiences [5, 20]. Researchers have been trying to understand the duality of social media concerning health [17]. SN, including wearable devices, would be a new paradigm for the betterment of humanity. Machine learning methods like RF, SVM, and CNN, which are used to collect and classify data from social media, have been used by many researchers to predict anxiety and depression. Various techniques have been used for encoding text, such as topic modelling, BoW, and TF-IDF; With the best result, all of these classifiers have a maximum accuracy of around 78%. Using machine learning to make medical diagnoses has led to much progress in healthcare over the past ten years. Early detection of depression is a major hurdle in effective and timely treatment. We believe our findings and methods will help develop tools for identifying the onset of major depression for use by healthcare agencies; Or on behalf of individuals, enabling those suffering from depression to be more proactive about their mental health.

With the help of social network services and cutting-edge technology, we can track, collect, and measure real-time medical data from patients. Using online social networks (OSNs), patients can also get publicly available information that plays an active role in making decisions about their health and educating themselves. Knowledgeâpatient engagement with others actively participating in decision-making; social networking services have a lot of potentials and can be useful tools for healthcare services. In conjunction with wearable devices, these online services facilitate access to information that reduces costs, research aids, and improves the overall healthcare system [9]. Hospitals have recently started using blogs to collect comments, client feedback, and more in-depth stories about patients' feelings. A healthcare provider could use the information to improve its services and market itself to potential customers who value feedback from past patients. The use of social media in healthcare poses some risks [14], but researchers are working to reduce negative side effects [18].

Network phenomena are getting more attention in fields like engineering and healthcare. As Uddin et al. [24] have proposed a deep learning model based on LSTM and RNN to find depression early on by analyzing huge textual datasets already set up by medical and psychological experts. In this experiment, they achieved an overall accuracy of 86%. Similarly, Yadav et al. [25] have applied ML algorithms to survey data and got around 82% accuracy. They used four different classification techniques, such as KNN, DT, RF, and MLR (Multimodal Logistic Repression), and also used some techniques like Bagging Boosting and Stacking. In the same way, Alsagri and Ykhlef [2] have built their model based on users' Twitter profiles and tweets to predict whether a particular user is depressed. The author used different classification techniques; among them, SVM worked well with 77% overall accuracy. Priya et al. [15] have to predict depression using different techniques of machine learning; For that, they have used other classification techniques, among which Random Forest works well with 73% accuracy. They used three different datasets that they got from Google. These datasets were not balanced, so they also used ML

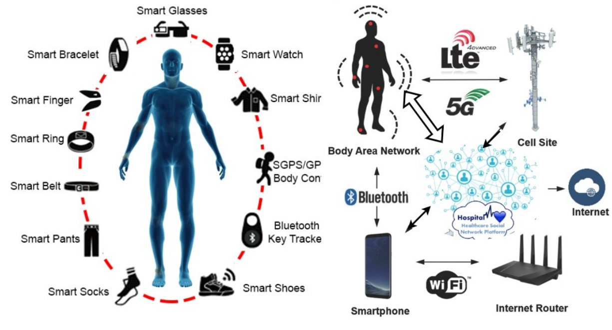


Figure 1: Glimpse of Wearable Devices by Humans

techniques to make them more balanced.

Kharel et al. [8] have explored the existing multi-modal fusion of audio, video, and textual data for depression prediction using machine learning. similarly, Chikersal et al. [4] have applied a machine-learning approach that uses data from fitness trackers and smartphones. They explored different feature sets and got around 85% accuracy. Kumar et al. [10] did the enhanced literature review and comparative analysis regarding the combination of social media and the Internet of Things. They have used Twitter as a tool for data collection from social media [13]. Their findings conclude that most researchers focus on artificial intelligence while discussing the Internet of Things and social media platforms.

2.1 Multimodal Medical Social Media

Social media, including multimodal or big data [16], and the Internet of Things are essential parts of daily life in the world we live in now. Both provide powerful, limitless communication platforms around the clock. During the last decade, people have used it to report many disasters or pandemics. Official bodies also use the same architecture to give current directions for what to do next. Also, online real-time monitoring of patient behaviour, health concerns, and system behaviour makes it possible to spot different levels of abnormalities that could lead to serious problems that need emergency care. Emergency and disaster medicine deals with various hard-to-solve medical, surgical, mental health, epidemiological, administrative, and communication problems. Technologies that boost cyber-physical connections between people, machines, and their surroundings include social media platforms and the Internet of Things. Over time, much data has been collected, helping to make emergencies and disasters less harmful. Let's mainly think about the use of social media by healthcare experts and doctors. We might think about three potential buckets of use: doctor-to-patient, doctor-to-public, and doctor-to-doctor. Doctors can use these platforms to educate patients and the public or exchange information. Social media is an incredible asset for influencing adult demographics. Healthcare professionals will also learn much about physical health if we share our health data. They will be able to provide us with timely and reliable expert medical advice.

2.2 Medical Wearable Devices

The term "*medical wearable devices*" or "*wearable technologies*" refers to tiny electronic gadgets or wireless communications capabilities built into or attached to clothing, accessories, or other items worn on the human body or even more invasive versions like microchips or tiny tattoos. The next generation of wearables will include a variety of smart clothes, wearable industrial equipment, and devices for augmented, virtual, mixed, and enhanced reality in addition to fitness trackers, smartwatches, on-body cameras, heart rate monitors, and eyewear, as shown in Figure 1. Modern technologies like smartphones, smart wristbands, social media, m-Health, and mobile apps are being used more often in the medical field due to features like low cost, usability, and portability.

Software and apps have turned them into personalized health clinics. Due to the advancement in information technology, all the devices in the healthcare industry have been digitalized. These digital devices enable us to live better and more comfortably. Therefore, people use various devices, such as smartphones and wearable sensors, daily. Smartphones and wearable devices contain sensors that can be used to obtain huge real-time monitoring of patients.

The pandemic highlighted the value of smartwatches for monitoring health [6]. For example, some smartwatches now have optical sensors that use photoplethysmography (PPG) to measure changes in blood volume and composition in real-time. With the arrival of wearable technology, it looks like we're almost there when it comes to technology. Google Glass, Smart EyeGlass, and various other devices When our glasses can take a picture or record a video and send it to our preferred social media site in a fraction of the time. The coming wearable tech revolution will take us into the humanities.

Also, digital devices create a huge amount of healthcare data, which the current systems can't store and process well enough to use for accurate monitoring. Moreover, combining multimodal information and extracting valuable information from healthcare data efficiently has become a new challenge for the existing healthcare monitoring systems [1]. Here the problem is how we can utilize these multimodal data generated by wearable medical devices. Much information, such as height, weight, and calories, is gathered by everyday activities, sleep patterns, and other factors, which are the most important factors of a person's health. Doctors and other medical experts are attempting to benefit from analysing such data, which aids in understanding the illnesses and cases impacting a certain community or nation.

2.3 Social Internet of Things (SIoT)

Social media has changed the world by connecting billions of people worldwide. This number is expected to grow by ten once new mobile computing networks, like 5G mobile networks, and new wireless services are widely used. When Internet of Things (IoT) services and social media come together, they create new social interactions that could help build a smarter social world with IoT apps, which refers to the *Social Internet of Things* (SIoT) [7]. Here, all smart objects are socialized and connected to social media. The devices can monitor, post, and share information automatically and regularly. To do this, new data fusion algorithms and AI techniques will automate decision-making and make it easier for smart objects to talk to each other and work together. These smart services and apps would effectively track and analyze social media data. SIoT techniques are feasible or even more reliable in healthcare.

Social media monitoring and the Internet of Things go together like peanut butter and jelly. The research community worldwide is looking for an easy way to listen to, watch, and analyze data from social media. IoT is poised to bring social media into the healthcare domain. Patients can now associate with the best health specialists available effectively, and IoT-powered social media interactions will help them. On the other hand, healthcare professionals will have all the information from the patientâs health records. IoT gives them an easy way to collect social data that doesn't waste their time or energy; hence, it has quickly captured the attention of social giants and organizations. Today, the Internet of Things is on its way to shaping the world into a better and more secure place. Using social media sites to make the IoT work better opens more and more doors for entrepreneurs and research communities. IoT has to be discussed while talking about the future of social media. Mobile traffic is a clear example of this. The network assists drivers in real-time travel optimization by connecting internet-connected cellphones to traffic signs, cameras, people, data, and other technologies. We could talk about many different things, but let's concentrate on the uses in medicine and healthcare.

3 Datasets and Processing

Several datasets are publicly available from social networking and Internet of Things points of view, but very few are existing datasets based on SIoT. Hence, we have considered two different but interrelated datasets from Kaggle; One from a social network and another from IoT. We performed some pre-processing on both datasets to build an accurate ML-based framework.

3.1 Data Sources

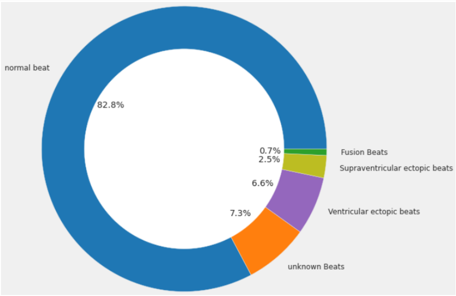
A combination of online social media and wearable devices would be a great way for the medical field to monitor diseases like diabetes and heart disease. For the multimodal social-medical system that uses wearable devices, we looked at two benchmark datasets that people tend to ignore, which can lead to other serious diseases. Blood pressure monitoring and depression (including anxiety and stress) are frequently overlooked daily. Hence, we considered blood pressure, anxiety, and prediction for our experiments.

Kaggle's ECG: Heartbeat Categorization dataset was used to classify heartbeats as normal or abnormal. 109446 samples were looked at and put into five subgroups: normal beat, supraventricular premature beat, premature ventricular contraction, the fusion of a ventricular and regular beat, and unjustifiable beat. Here, the sampling frequency is 125 Hz.

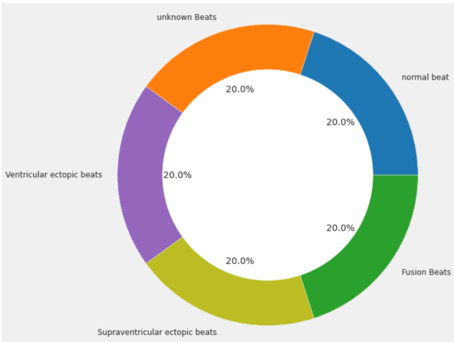
Depression: This dataset contains 1.6 million tweets extracted from Twitter through the API. The dataset includes three different types of statements: negative, positive, and neutral, with six different attributes. Our tests only looked at harmful and helpful social media posts to identify whether the person was depressed.

3.2 Media Prepossessing

We, in this work, did the end-to-end preprocessing and training part. First, we took random pieces of text from the benchmark dataset and removed attributes that weren't important. Then, we used the regex operation to remove all punctuation marks, Twitter handles, links, numbers, and special characters. We removed all stop words and performed tokenization to normalize the textual information. We applied the porter-stemmer function of the *nltk* library and removed all small words. Finally, use word clouds to visualize the most common positive and negative words, as shown in Figure *Negative Words*.



(a) ECG Dataset without normalization



(b) Normalized ECG Dataset

Figure 2: Before and after normalization ECG data

We selected only 20% random sampling from the whole dataset for our experiments due to the restriction of local machines and a vast amount of data (16M). We split the dataset into a 7:3 ratio for training and testing purposes. For training and testing, we use four different classifiers as XGBoost, Random Forest (RF), Logistic regression (LR), and Support Vector Machines (SVM). For XGBoost, we set the Max depth to 6, the number of estimators to 1000, and the number of threads to 3; similarly, for Random Forest, the number of estimators is 1000, and the random state is 42; and the Linear kernel for SVM.

Similarly, we performed a data transformation process for the ECG dataset, changed all floats values into an integer, removed special characters, and set six types of labels as *Normal beat*, *Supraventricular premature beat*, *Premature ventricular contraction*, *Fusion of ventricular and normal beat*, and *Unclassifiable beat*. Then we checked the balancing factor of data as shown in Figure 2. Before building and executing the model, we have visualized the different beats of ECG data shown in Figure 3. Further, we check the data distribution and shuffle it, then split it for training and testing, where 75% of the data is used for training, and the remaining 25% of the data is used for testing. We used Residual Networks for building the model and glorot_uniform

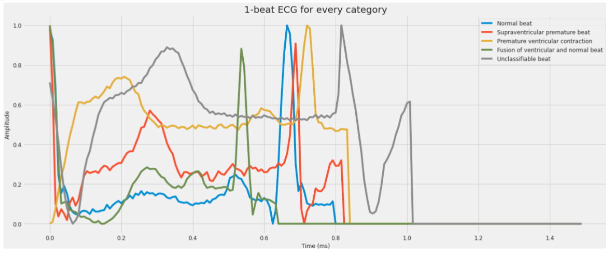


Figure 3: Different categories of ECG beat

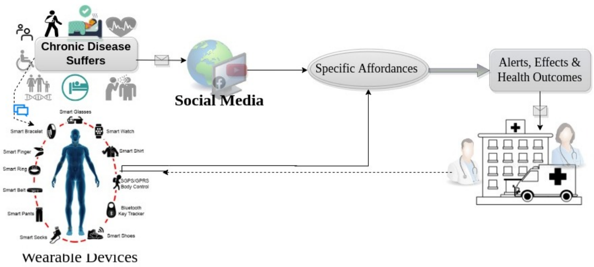


Figure 4: Abstract SIoT ML Architecture for Healthcare

for uniform data distribution; '*relu*' activation function and *BatchNormarlization* were used to generalize and stabilize the model. We execute our model up to 100 epochs with Early Stopping regularization techniques and Max pooling to select a max element from the feature map. We randomly selected data samples from the dataset for validation purposes and got excellent results.

4 The Proposed Unified ML Architecture

SIoT has turned into personalized health clinics, which makes it easier to keep track of patients' important information and provide knowledge to them. But the problem with SIoT is that it generates gigantic amounts of unstructured, multimodal, multi-linguistic, unstructured, or unlabeled big data. On the other hand, using old architecture and old machine learning techniques, processing Big data with good accuracy is not possible. Therefore, a novel framework is needed for healthcare monitoring and alert system based on knowledge fusion that improves accuracy and efficiency. Hence, we have proposed a novel unified framework to deal with such issues and full fill our requirement as shown in Figure 4.

The prime objective of the proposed framework is to generate alerts and monitor the patient's chronic disease. Still, from a broad perspective, this can be used in any circumstance for healthcare. This framework has mainly four sub-blocks with well-defined functionality. The first block is signal generation from the patient side. This can be done automatically by automated wearable devices or using social media accounts. The second block is the most important part of this framework, where specific actions will be taken based on information. In the next block, filtered information will be sent to healthcare providers, from which experts can advise patients or control automated wearable devices.

Figure 5 is the extended version of the Unified Architecture as shown in Figure 4. Here, we elaborate functionalities of the Unified model with proper input and outputs. At first multimodal data came into a cloud as big data from social media or wearable devices, where we used certain types of pre-processing to convert multi-modality data into single modalities. On uni-modality data, we perform preprocessing based on modalities. We filter out useful attributes and drop out relevant attributes after applying PCA. On textual data, we applied Transformer-based BERT (Bidirectional Encoder Representations from Transformers) architecture and Convolutional Neural Networks (VGG-19) on visual contents. We concatenate preprocessed uni-modality data using Hybrid fusion (Knowledge Fusion) techniques to build multimodal feature sets (MFS). This MFS goes to the AI sub-model, where we use Deep Learning to learn representation from MFS. AI model generates useful information and automatically sends relevant information or notifications to healthcare providers. Based on alerts or notifications generated by the AI sub-model, healthcare providers take major actions to prevent the loss of human lives.

4.1 Knowledge Fusion

After linking records, knowledge fusion merges all data origins for a given entity. As humans gather information from various sources and combine it to form knowledge, different information modalities should be combined for AI to make accurate predictions. SNN, RNN, and CNN architectures, such as long short-term memory (LSTM) and its variants, transformer-based architecture, can be used to fuse these data modalities.

5 Results and Analysis

The experimental findings demonstrate how the suggested architecture works for healthcare using social media, wearable medical devices, IoT and machine learning. The results show that the proposed architecture successfully recognizes updated personal health-related information.

Table 1: Comparative results of the proposed framework on depression dataset

2***Method**	2***Acc**	**Depressed**			**Not-depressed**		
		Pre	**Rec**	**F-1**	**Pre**	**Rec**	**F-1**
MLADD [2]	0.82	0.74	0.85	0.75	-	-	-
DDLS [4]	0.82	-	0.78	-	-	-	-
PDRS [25]	0.81	-	0.78	-	-	-	-
RF	0.64	0.63	0.62	0.65	0.65	0.66	0.63
SVM	0.70	0.84	0.77	0.73	0.74	0.66	0.70
XGB	0.76	0.74	0.75	0.76	0.77	0.76	0.80
LG	**0.84**	**0.86**	0.85	0.84	0.82	0.83	0.84

5.1 Experimental Setup

Here, we used a GPU-based local system with 4 GB memories and the latest Python package. The *TensorFlow* framework analyzes data using GPU resources by utilizing the *Keras* API and other packages provided by Python libraries such as Sklearn, Pandas, Numpy, Matplotlib, CuPy, and others. We used various classifiers and neural networks, as well as hyper-parameters that were tuned for generalization ability. We trained our proposed framework on 'Depression' and 'ECG' datasets.

5.2 Performnace Evaluation

Table 1 demonstrates the performance of the proposed framework in terms of Accuracy, Precision, Recall, and F1 Score for both depressed and cheerful on the depression dataset. The first few rows of Table 1 demonstrate performances achieved by different models; the remaining rows describe performance gained by our proposed framework, whereas highlighted indicates maximum performance. Here we have shown the comparative analysis of the proposed framework. The first three rows of the table have some black space "-" in columns that the authors do not mention; they focused only on accuracy, whereas MLADD, DDLS, and PDRS are just the naming convention used to indicate the comparative title of the papers. Finally, we plot the AUC-ROC curve for Accuracy and Loss for training and testing data.

At the beginning of our experiments, we used Random Forest classifiers because they produce good predictions that can be easily understood and handle large datasets easily. Here we set the hyper-parameter for RF as 1000 for the number of estimators and 42 random states to control randomness for the learning model; unfortunately, on the depression dataset, RF has achieved only 64% Performance of accuracy as we can visualize from Table 1 and same the results from Figure 6(a).

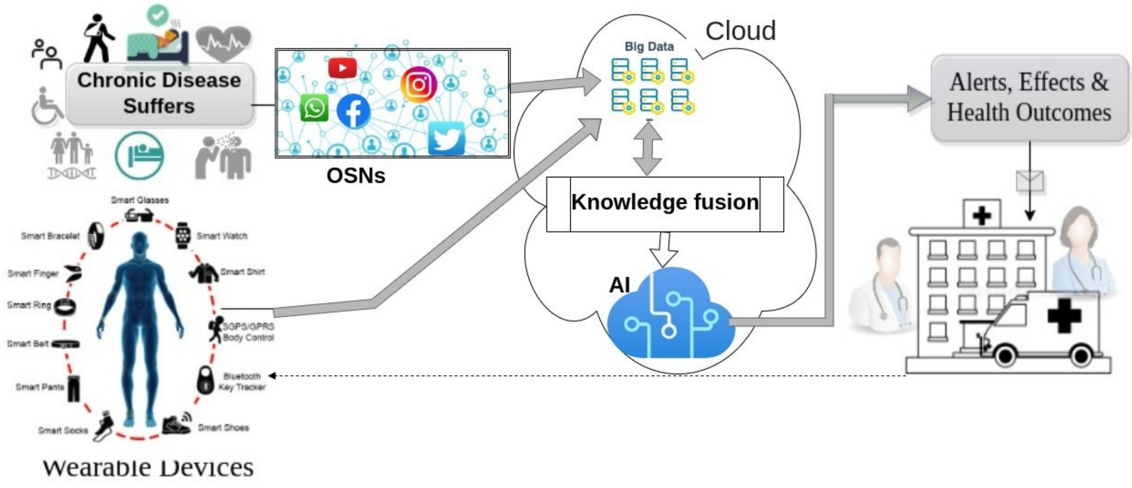
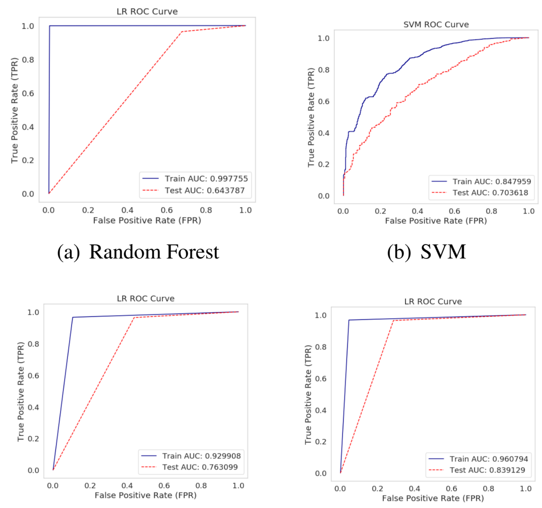


Figure 5: A Unified SIoT ML Architecture for Healthcare

Here, RF was taking too much time on training and testing, and accuracy was not up to par as expected. Hence, we replaced RF with a support vector machine. Using SVM, we got better precision, recall, F1-Score, and accuracy, shown in Table 1. The accuracy of SVM was around 70%, which is comparatively 6% better than RF, as shown in Figure 6(b).In the search for better classification, when we used the XGBoost classifier, then 76% accuracy was much better than previous classifiers in terms of performance. Finally, we applied Logistic Regression due to easy-to-implement and efficient training timing and got 84% accuracy, which can be easily visualized from Figure 6(d). XGBoost got better results in other performance matrices that can be seen in Table 1 and Figure 7.

The accuracy curves show the ML model's performance throughout the training and validation operations for training and validation data 6. These curves are essential tools for monitoring an ML model's performance while it is trained and making sure it can properly generalise to untried data. To compare the model's performance on the training and validation datasets, these two curves are often shown on the same graph. If the training accuracy is much higher than the validation accuracy, the model may need to be balanced more with the training data to generalise appropriately. If the validation accuracy exceeds the training accuracy, the model may need to be more balanced and suit the training data.

The performance of a machine learning model throughout the training and validation phases graphically visualize by the AUC-ROC curve 7. Area Under the Receiver Operating Characteristic curve, or AUC-



(a) Random Forest (b) SVM

(c) XGB Classifier (d) Logistic Reg

Figure 6: Training and Validation Accuracy Curve on Depression dataset

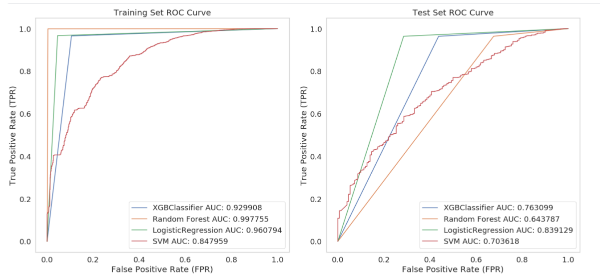


Figure 7: Training and Testing AUC-ROC Curve on Depression dataset

ROC, is a popular assessment statistic for classification model evaluation. It compares the true positive rate (sensitivity) against the false positive rate (1-specificity) for various threshold settings. The percentage of correctly identified positive samples is represented by the true positive rate, while the false positive rate represents the proportion of mistakenly classified negative samples. The shape of this curve reveals how effectively the model generalizes to fresh, untested data. It helps determine if the model over- or under-fits the training set of data.

Similarly, in another experiment, we used ECG dataset on the same architecture to check the proposed framework's performance and utility; these datasets can easily be obtained from any wearable device (a smartwatch) and shared on any social platform. Here we have tried to classify five beats of ECG data to identify abnormalities for warning. These beats include 0 (Normal beat), 1 (Supraventricular premature beat), 2 (Premature ventricular contraction beat), 3 (Fusion of a ventricular and normal beat), and 4 (Unclassifiable beat). We have used a Residual neural Network (ResNet) to continue this experiment because it avoids negative outcomes while increasing network depth.

At first, we split the dataset into training and testing with 75% and 25%, respectively and then standardized the data values into a standard format. Finally, we construct the model using ResNet with an input of 256 and an output of 5. We have mainly used three fully connected layers with *relu* activation and softmax function. We set parameters for ResNet as batch size 512, loss =' categorial cross-entropy, and Optimizer is Adam. We have used Early Stopping criteria and executed up to 100 echos. Due to the Early Stopping criteria, we were getting the best performance of the model at an early stage.

Accuracy and loss curves are visually shown in Figure 8. The left side of Figure 8 represent accuracy on training and validation data, whereas the right side of Figure 8 represent training and validation (testing) loss. These curves show how well the model performed throughout training and how the losses vary over time. It learns from the data and applies generalization to the new data to improve the model's performance. We observe from Figure 8 that the initial training and validation accuracies were 90.5% and 94%, respectively, which increased more than 99% after some epochs. In contrast, starting losses were 0.9 and 0.68 for training and validation, respectively, down toward zero, and the final loss is to 0.1 for both training and validation.

Table 2 shows the performance of the proposed model in terms of precession, recall, and F1-score.

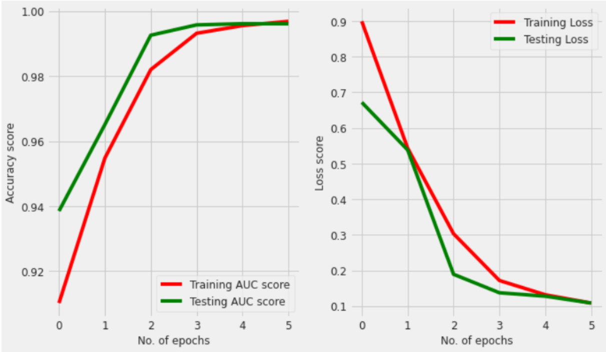


Figure 8: Accuracy and Loss while Training and Validation of Model on ECG Dataset

Table 2: Comparative results on ECG data

Levels	Pre	Rec	F-1	Support
0	0.98	1.00	0.99	18118
1	0.96	0.72	0.82	556
2	0.97	0.93	0.95	1448
3	0.92	0.67	0.77	162
4	1.00	0.95	0.97	1608

Here, we observe the performance of individual beats. Level 4 beat having 100% precession and 0 having 100% recall, whereas level 0 also has got 99% of F1-Score.

In ML classification tasks, the accuracy of a model's predictions over numerous classes or categories is evaluated using a multi-class confusion matrix 9. It thoroughly describes how well the model categorizes occurrences into various classes. It also generates measures like accuracy, precision, recall, and F1-score. By observing the Figure 9. Observing the confusion matrix, we find that the beat level having zero (0) has excellent performance with 100% true prediction. In contrast, the level 3 beat has the lowest 70% true prediction.

5.3 Challenges and Limitations

The proposed architecture has important practical ramifications in the real world and the potential to be used in real-time to enhance patient care, monitoring, and general public healthcare. By combining social network platforms with wearable devices, healthcare professionals will be thoroughly aware of patients' health states, behaviour, and social contacts. The framework will provide the ability to continuously monitor patients' vital signs, physical activity levels, sleep patterns, and other real-time health-related data. This integration,

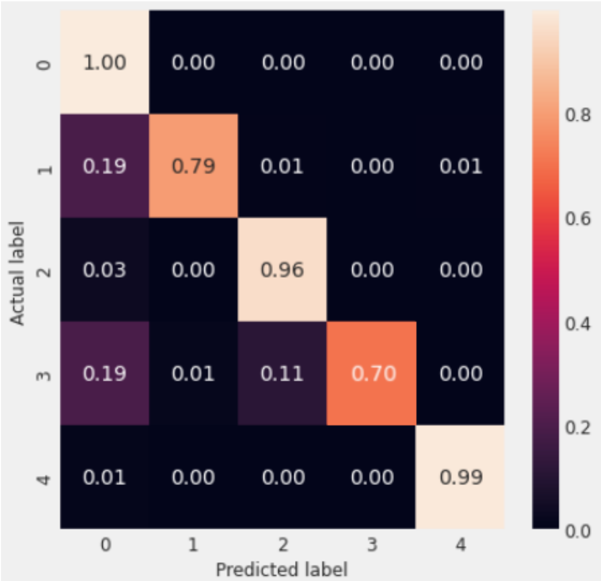


Figure 9: Confusion matrix on ECG dataset

improved care coordination, and patient involvement make personalized and proactive healthcare interventions possible. Patients will gain knowledge from the network's collective experience, get feedback on their health-related behaviours, and find encouragement to follow treatment regimens.

Designing and deploying such a framework requires careful consideration of scalability. To successfully meet the demands of a more significant user population and provide dependable and timely healthcare services, it is essential to ensure the system can expand data volumes, user bases, linked devices, and network traffic; however, several issues and restrictions need to be resolved: such as data security and privacy, Interoperability and standardization, user engagement, and data overload balancing. In this work, we have used social media for symptoms of depression and IoT for collecting sampled time-series data and synchronization. Therefore, the IoT subsystem in this framework is limited to collecting numeric and textual data collected through wearable devices.

6 Conclusion

This paper explores and implements the idea of using social networking, the Internet of Things, machine learning, and Big data to collect and process online data to identify severe anomalous data for alerts and warnings. The proposed framework of SIoT (association of SNs and IoT) will be able to collect various information related to chronic disease and prevent life loss by providing earlier warnings, and it will also flash alerts to healthcare providers on urgent appeals that could potentially help people in need. Here we have focused on multimodal knowledge fusion that could be collected from different sources like social networking sites and wearable devices. We have used two different datasets collected from two different environments social networking sites and wearable devices. This research reasserts that people with depression spend less time with others, have more negative feelings, pay a lot of attention to themselves, and worry more about their relationships and health. The proposed framework efficiently processes both datasets and identifies anomalous data. Hence this type of framework will be lifesaving technology in upcoming future.

In the future, such a framework may be extended to a collection of time-series pulses and CT-Scan for 2D images. In SIoT, technology for data analysis and user-centric strategies constantly improve that must be incorporated with the proposed framework for efficient use in healthcare.

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