Framework towards critical event classification of bipolar disorder in internet of things ecosystem

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Article Info

ABSTRACT

Bipolar disorder is quite a challenging mental illness which encounters substantial degree of challenges in confirmed diagnosis irrespective of modernized increasing pace of development in medical science. With the evolving standards of automation in healthcare section integrated with advanced technology, it is imperative to anticipate a reliable on-line diagnosis of mental illness for a given scenario of internet of things (IoT). Review of existing methodologies showcases a wide gap between enormous research work towards identification of bipolar disorder and only few studies towards on-line diagnosis considering patients residing in smart city. Therefore, the proposed scheme introduces a novel computational framework of an underlying architecture of an IoT that not only facilities an effective and simplified transmission of multimodal data autonomously from the patient forwarded to clinical analytical unit but also perform a multitier classification using deep neural network. The study outcome exhibits proposed scheme to offer better data transmission with higher accuracy performance in contrast to existing prevalent schemes.

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1. INTRODUCTION

Bipolar disorder is a typical form of mental illness that results in uncertain and unusual mood swings ranging from mild to critical symptoms [1]. With the increasing pace of development in medical science, the accomplishment of treating mental illness is still a bigger challenge [2]. At present, there are various forms of screening mechanism towards confirming the exact state of bipolar disorder; however, the process of such confirmed diagnosis is tediously time consuming and demands frequent and regular visit with psychiatrist [3], [4]. The prime challenges towards confirmed diagnosis of bipolar disorder are mainly overlapping symptoms, presentation of complex symptoms, issues in formulating criteria of diagnostics, condition of comorbidity, delays in diagnosis, and absence of any objective test of diagnosis [5]–[10]. Apart from this, there is an increasing transformation of physical diagnosis to on-line diagnosis with an evolution of automation standards in healthcare [11] and internet of things (IoT) [12]. At present, there are various studies where sensing technologies of IoT has been used for online diagnosis of various diseases [13]–[15]. However, there are very few to find in the use case of mental illness. In order to develop such on-line diagnosis scheme, the first and foremost essential aspect is to design a generalized communication scheme which can track the event of severity on the basis of captured information from various sensing devices and other technologies [16]. The biggest hurdle in this case is to deal with existing traffic-based issues in IoT routing [17]. Even if this data transmission scheme is developed, the next hurdle will be to perform analytical

operation to generate the actual conformed diagnostic result. At present, artificial intelligence and its hierarchical types are preferred to solve such issues; however, they have not yet been assessed for transmission and analysis together. Therefore, the contribution of the study are as follows: i) a novel framework of identification and classification of bipolar disorder is constructed using physiological data and mobility-based data, ii) a novel IoT environment is constructed where the data is collected, filtered, and forwarded to gateway node which is further subjected to a novel analysis towards conformed diagnosis, ii) a unique data transmission scheme using single/multihop communication is developed which can offer transmission of aggregated data over prioritized and regular channel in IoT, iii) the unique and yet simplified deep neural network is deployed which is capable of classifying into healthy, bipolar disorder type-1, type-II, and schizophrenia, and iv) a benchmarking is carried out by comparing the proposed scheme with conventional routing scheme in IoT as well as frequently used predictive approaches.

This section is a continuation of briefing of existing methodologies used in confirmed screening and classification of bipolar disorder [18]. Shao *et al.* [19] have presented a unique predictive model towards diagnosing bipolar disorder using deep neural network considering temporal images as data. Adoption of neural network-based predictive diagnosis is also carried out by Luján *et al.* [20] where radial basis function has been used along with fuzzy logic. Adoption of machine learning towards predictive analysis of anticipated risk factor associated with bipolar disorder is carried out by Huth *et al.* [21]. The study has used linear support vector machine (LSVM) in order to make the classification using radiological images of brain. Similar form of study is also carried out by Suen *et al.* [22] where machine learning is applied to data developed from personal traits of mood rating scale based on social and demographic information. Frau *et al.* [23] have used slope entropy in order to perform classification on the basis of actigraphy-based data. A unique framework towards diagnosis of same mental illness considering use case of elderly patient is carried out by Frisardi *et al.* [24]. Kondo *et al.* [25] have used multivariate analysis in order to investigate type-I bipolar disease. The idea of this work is to carry out pattern recognition for emotion regulation data. Notable study contributed by Tian *et al.* [26] have used machine learning in order to investigate the suicidal tendencies associated with bipolar disorder. The authors have used k-nearest neighbor approach on radiological images of brain to carry out this analysis. Adoption of deep learning is discussed in work of Li *et al.* [27] where radiological images of brain is subjected to convolution neural network (CNN). The idea is to carry out classification on the basis of healthy control, bipolar disorder, and psychosis in preliminary stage.

Apart from the studies, various online-diagnostic schemes in IoT have also been reviewed. The idea is to assess the feasibility of data transmission and conform diagnosis of mental illness using IoT. Ross *et al.* [28] have presented a clustering approach for prediction of depression in IoT considering accelerometer features. Further, Forchuk *et al.* [29] have presented discussion associated with usage of smart technology towards monitoring patient with mental disorders using quantitative analysis of data captured during interview process. Apart from this, there are various other studies which were witnessed to highlight the supportability of IoT towards diagnosis of mental illness viz. monitoring mental state using wearable sensors [30], [31], discussion of various pros and cons associated with adoption of IoT towards diagnosis of mental illness [32], rise of automation standards in healthcare [33], and inpatient care by adoption of schemes using digital transformation [34], [35].

There are also certain serious attempts where multimodal signals have been utilized towards diagnosis of mental health in recent studies. Alwakeel *et al.* [36] have used multiple forms of sensor data in context of smart city in order to identify mental disorder. Baki *et al.* [37] have presented a study using data of visuals, linguistic, and acoustic in order to classify severity of mania. Adoption of semi-supervised learning scheme with ladder network is used for classification as noted in work of AbaeiKoupaei and Osman [38]. Further, Cao *et al.* [39] have used CNN and auto encoder on the feature from extracted text and acoustic modalities. A closer look at the existing review of literature exhibits some missing gaps: i) there is no standard benchmarked framework for online diagnosis of bipolar disorder and its types in IoT, ii) the modelling of predictive mechanism doesn't include the transmission or data acquisition process, iii) existing studies of multimodalities are few to find and are found with very few classes of signals derived which potentially limits reliability of predictive outcomes, iv) there is no cost-effective and lightweight analytical model towards instantaneous diagnosis of mental health irrespective of evolution of automation standards in healthcare relating to IoT. The organization of this manuscript is as follows: section 2 discusses about adopted research methodology. Section 3 presents discussion of accomplished benchmarked outcome of study, while section 4 discusses about conclusion.

2.   RESEARCH METHODOLOGY

The prime goal of the proposed research work is towards developing a novel computational model which can be used for online diagnosis of critical mental abnormality like bipolar disorder in the context of IoT. The overall system is designed to arrive at autonomous diagnosis process using simplified and

cost-effective information capturing units. An analytical modelling is carried out towards this process which is shown in Figure 1.
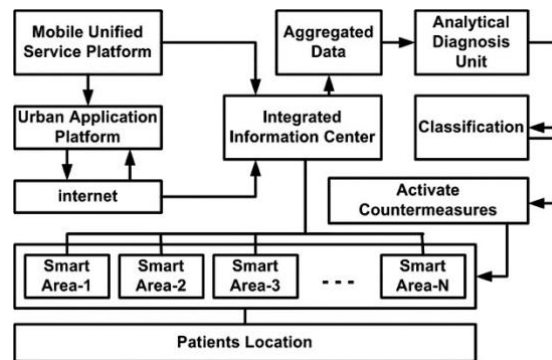

Figure 1. Adopted methodology for online diagnosis of bipolar disorder

According to Figure 1, the overall scheme performs in following manner: the study assumes that all the patient resides within a smart city zone of an IoT where they are equipped with a normal fitness band as well as smartphone. The core idea of the study is to harness the sensing capability of these two sensing devices to capture the multi-dimensional information associated with representing state of the patient with respect to a scale of bipolar disorder. The first part of the implementation has emphasized towards introducing a novel communication model which autonomously collect and filter sensed information, aggregate them and forward to the gateway node. The aggregated information from the gateway node is further forwarded to analytical unit hosted in cloud environment where a deep learning approach is used for further classification. The selection of sampling rate of the information captured from these devices is subjected to alteration which eventually makes the proposed scheme more applicable to be used on practical ground of operation. Apart from this, the deep learning approach used in this process is artificial neural network owing to its capability to offer a good balance between problem solving capability and justified accuracy. The scheme also introduces a mechanism of filtering out unnecessary parameters in neural network which makes the scheme further more lightweight with extremely less computational burden. In simpler sense, the scheme presents a novel decision making and predictive process which can offer almost an instantaneous response when encounters a criticality state of bipolar disorder without an intervention of any human. The next section elaborates the system design involved in this process. This section presents discussion about the system designed involved in proposed study. It should be noted that primary aim of the overall process is to ensure the timely identification of the critical events autonomously using multimodal sensing data from the patient's body. This aggregated data is further subjected to analytical method in order to investigate the state of severity of the bipolar disorder reported by the devices attached to the body of a patient. For this purpose, the proposed scheme is designed considering two essential modules i.e., module for performing communication of the sensed data to the healthcare unit and module for performing analytical operation over the aggregated sensed data.

2.1. Schema for communication of sensed data

The prime aim of this module is to ensure that irrespective of the location of patient, their information should propagate via a planned network in IoT exclusively emphasizing on healthcare sector. The notion of this algorithm is also towards identifying the significant form of an event of critical nature in bipolar disorder to be offered as a priority channel for propagation via integrated sensory, cloud, and IoT based environment. The agenda of this algorithm is towards formulating a novel, highly customized, flexible communication scheme. The steps of the proposed algorithm are as follows:

Algorithm for communication facilitation
Input: u_{max} (total number of user), $u_s/u_m/u_d$ (users from small/medium/dense region)
Output: t_{data} (transmitted data)
Start
1. For $i=1:u_{max}$
2. $u=[u_s, u_m, u_d]$

3.   If $\lambda_{mm}>\tau_1$
4. $u\rightarrow g_{node}(msg)$
5. $u_s\rightarrow sh(g_{node}(msg))$
6.   If $t_{ev}<1$
7. $u_m\rightarrow sh(g_{node}(msg))$
8.   Else
9. $u_m(ts_{min})\rightarrow sh(g_{node}(msg))$
10.   If $d_{ud}>d_{max}$
11.   If $d(ud{\sim}gn)>1$
12. $u_d\rightarrow mh(g_{node}(msg))$
13.   Else
14. $u_d\rightarrow sh(g_{node}(msg))$
15.   End
17.   *Alloc* $p_{ch}\rightarrow u(\lambda_{mm}>\tau_2)$
18.   End
19. $t_{data}\rightarrow gn$ transmitted data
19. End
End

The proposed algorithm for communication takes the input of total number of user u_{max}, and users from small/medium/dense region ($u_s/u_m/u_d$), which after processing yields and outcome of transmitted data (t_{data}). The term *user* refers to the patient who is assumed to residing on different location within a new design of an IoT environment as shown in Figure 2. The discussion of the proposed algorithm is carried out with reference to IoT deployment scenario presented in Figure 2. The study algorithm considers its implementation applicable for all its users' u_{max} (Line-1). The user u is further categorized on the basis of their population concentrated in different location of an IoT. The first form of user u_s is considered as a single patient residing in one location, while the second form of user u_m is considered as 2-3 patients residing in specific location. Similarly, the user u_d is considered to be a region concentrated with multiple number of patients (say more than 10). Hence, the user u can be specified as a matrix with defined elements of small-concentrated users u_s, medium-concentrated user u_m, and densely-concentrated user u_d i.e., $u=[u_s, u_m, u_d]$ as exhibited in Line-2. Furthermore, all the users u are assumed to be attached with different forms of sensing devices (both attached and non-attached) and smartphones sensors, which is capable of performing consistent monitoring of critical (type-I bipolar disorder) and non-critical event (type-II bipolar disorder). All these devices capture multimodal information λ_{mm}, which are further compared with the primary threshold τ_1 for preliminary confirmation of types of bipolar disorder (Line-3). For this purpose, the proposed system makes use of our prior model [40]–[42] to identify the initial determination of bipolar disorder in order to arrive at value of primary threshold τ_1. In such case (Line-3), all the users u are permitted to forward their multimodal aggregated information *msg* to the gateway node (Line-4).
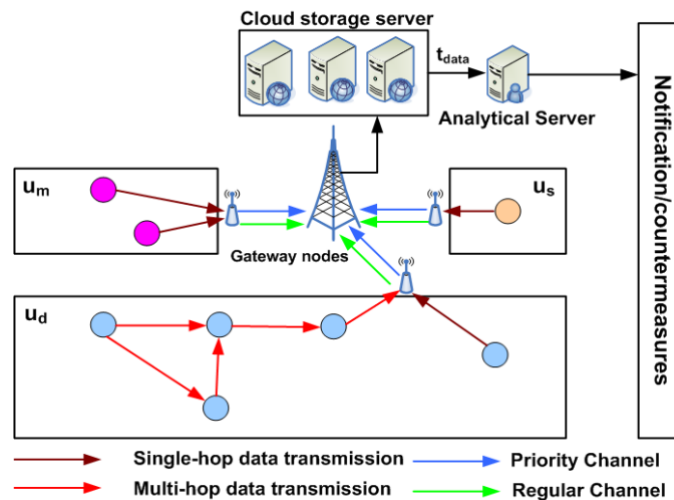

Figure 2. Proposed IoT environment for data communication

Users belonging to smaller density u_s forwards the data using single hop sh transmission to propagate msg to the gateway node gn (Line-5). A different methodology is adopted for the users belonging to medium density i.e., u_m for data transmission. In such case, time of event t_{ev} is evaluated for all the users u_m (Line-6). If the time of event t_{ev} is found to be lesser than probability value of 1 representing lesser number of critical event than the user u_m forwards msg using single hop concurrently (Line-7). Otherwise, the system checks for the minimal value of timestamp ts_{min} representing the freshly arrive data where the user u_m forwards data one by one using single hop (Line-9). The next type of data forwarding strategy is developed exclusively for densely-concentrated user i.e., u_d. In such case, the scheme computes a distance d_{ud} among all the nodes u_d and compare them with maximum distance d_{max} (Line-10). The initialization of the maximum distance can be carried out considering the extreme point of transmission range of all the devices where it needs higher number of resources to be allocated to forward the data to gateway node. The algorithm finds distance between such node u_d and gateway node gn and if this distance is found to be more than higher probability limit of 1 (Line-11), than the algorithm let the user u_d to adopt multihop propagation mh to forward the information msg to the gateway node gn (Line-12). Otherwise, the node u_d performs single-hop data transmission (Line-14).

The final part of the algorithmic implementation is associated with the channel of communication. For this purpose, the algorithm initially checks if the multimodal event value is found more than secondary threshold τ_2 for any type of users u than it allocates a priority channel p_{ch} for data propagation (Line-17). It should be noted that difference of primary threshold τ_2 and secondary threshold τ_2 is that former is associated with preliminary confirmation of bipolar disorder type while latter is associated with frequent and repeated events of bipolar disorder (especially type-I). Finally, the aggregated data t_{data} is transmitted to the gateway node gn (Line-19) and that completes this algorithmic operation. All the aggregated data are further forwarded by the gateway node and stores in distributed cloud storage units which are directly accessible by the healthcare unit where an analytical algorithm is executed further.

2.2. Schema for analytical operation over sensed data

This part of the model implementation is carried out within the analytical unit in cloud environment after it obtained the aggregated data t_{data} from the prior algorithm. The proposed study considers that these t_{data} is obtained from two different sources which is related to direct or indirect attachment with the body. As the proposed scheme introduces the concept of multimodal data which are combinedly studied in order to perform classification of bipolar disorder; therefore, the study considers the two types of data viz. i) physiological data p_d and ii) mobility-based data m_d. The physiological data p_d is considered to be the data obtained from smartwatch viz. body temperature, heartbeat, SPO2, and stress level. The mobility-based data m_d is considered to be obtained from various forms of sensors used in smartphones as well as from smartwatches e.g., three-dimensional acceleration, pedometer, surrounding temperature, and gravity. It is to be noted that none of these individual data types are same for both p_d and m_d and hence effectively formulates a multimodal event data. With reference of varied standard indicators [43], all these values can be standardized based on clinical protocols. As the proposed study is carried out in analytical research methodologies, these values can be amended suitably with any specific use-cases with respect to manufacturers or different standard values exercised in different countries. The algorithm takes the input of transmitted data t_{data} from prior algorithm that after processing yields an outcome of determined classes of bipolar disorder Cl_{final}. It is to be noted that the variable t_{data} represents aggregated data from multiple places encapsulated under a smart city of an IoT and hence the algorithm needs to consider all the values of t_{data} in order to arrive to conclusion towards classification (Line-1). The algorithmic steps are:

Algorithm for analytically classifying bipolar disorder
Input: t_{data} (transmitted data)
Output: Cl_{final} (determined classes of bipolar disorder)
Start
1. For i=1:t_{data}
2.   σ→f_1(i)
3.   σ(train$_{set}$)→o$_{dis}$
4. l_d→f_2(σ(p_d, m_d))
5.   For α_1~(α_2 && α_3)
6.   *Alloc n* layers
7.   For α_1~ α_2
8.   Alloc *m* layer | *m>n*
9.   End
10.   End

11. $p_w \rightarrow f_3(m, n)$
12. $Cl_{final}(p_w, \beta) \rightarrow class(\alpha_1|\ \alpha_2|\ \alpha_3|\ \alpha_4)$
13. End
End

The next step of the algorithm is to estimate density σ by using an explicit function $f_1(x)$ considering all the transmitted data t_{data} (Line-2). This explicit function $f_1(x)$ is responsible for perform estimation of density where finite quantity of standard distribution of t_{data} is appended with unknown attribute that finally generates data point. This operation is followed by computing log probability of the mixed data obtained from density estimation. In the following step, a training set of data $train_{set}$ is used over the outcome of estimated density in order to generate an optimal distribution o_{dis} (Line-3). In the next step, a labelled data l_d is generated by using another explicit function f2(x) considering the estimated density applied over physiological data p_d and mobility-based data m_d (Line-4). It should be noted that prior to generation of a labelled data, synchronization and normalization has been already carried out in this process.

The proposed scheme uses deep learning methods for this purpose with a customized layers in order to arrive at conclusive remarks. For this purpose, the scheme considers 4 different classes associated with considered mental disorder i.e., α_1, α_2, α_3, and α_4 to represents healthy, bipolar disorder type I, bipolar disorder type II, and schizophrenia respectively. The proposed scheme considers a use case where the class α_1 is compared with class α_2 and α_3 (Line-5). In such case, the system performs an allocation of the n number of layers (Line-6). Consecutively, the assessment is carried out towards comparing class α_1 and class α_2 only (owing to its higher severity) as shown in Line-7 followed by allocation of m number of layers by the deep learning approach (Line-8). It should be noted that proposed scheme uses $m>n$ condition to offer higher optimality of classification outcome.

In the consecutive process, the proposed scheme performs training operation using a function $f_3(x)$ with an input arguments of layers m and n in order to obtain previous weight p_w (Line-11). The operation carried out by the explicit function $f_3(x)$ is that it introduces a mechanism to eliminate all the connection of weights in deep network in order to minimize the dependencies towards storage size and maximize the computational speed during classification process. In simpler form, the function $f_3(x)$ is responsible for eliminating all the parameters that are not much in use over a parametric neural network in proposed scheme. Finally, the proposed scheme uses the previous weight pw and a method β in order to derive the class as an outcome of final classification Cl_{final} (Line-12). The overall mechanism of analytical operation is shown in Figure 3.
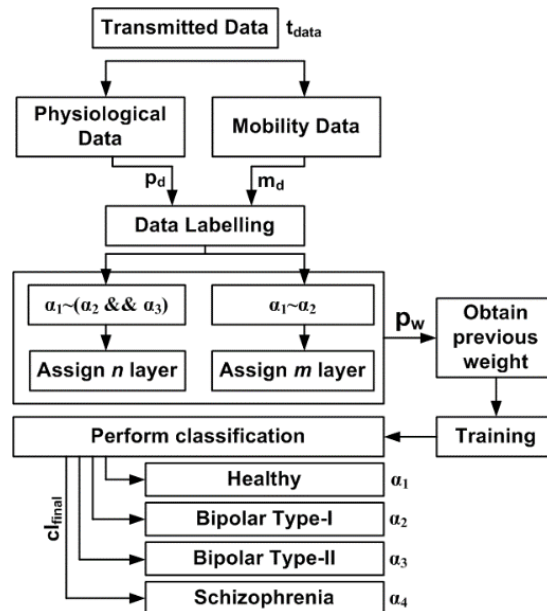

Figure 3. Analytical classification of bipolar disorder

From the Figure 3, it can be stated that proposed model using deep learning is meant for performing automated diagnosis of large number of patient's information associated with bipolar disorder. It will mean

that once the aggregated data t_{data} arrives in the cloud, the algorithm instantly becomes active as it takes this data as its input and after processing, the algorithm furnishes its final inference of respective class of bipolar disorder. This analyzed information can be then forwarded to respective healthcare unit or attending physician where they can undertake countermeasures to treat the patient in an event of severity. The significant contribution of the proposed system design is that it is quite progressive in its operation and less iterative. Further, by developing a sparse matrix of m and n order ($m \neq n$, and $m > n$) for both the types of input data (p_d and m_d), the proposed scheme offer not only higher but reliable score of accuracy of the predicted classification scores. Hence, a cost-effective transmission and analytical scheme is presented for diagnosis of bipolar disorder in context of IoT scenario. The next section discusses about the outcome obtained after implementing the proposed scheme.

3. RESULTS AND DISCUSSION

This section presents the discussion of the outcomes accomplished from the implementation plan discussed in prior section. One of the important parts of implementation is associated with dataset. At present, there are various publicly available origins of dataset for investigating bipolar disorder [44]–[48]; however, it doesn't match with the exact scenario of multimodal signals used in proposed study. Existing dataset deals with one type of data leading towards diagnosis whereas proposed scheme has considered multiple forms of data. In order to deal with this situation, the first part of implementation has considered 100 adult participants who were all equipped with Boat Xtend smartwatch and normal android smartphones equipped with motion sensors that can trap various information associated with mobility. Therefore, smartwatch has been used for collected body temperature-(A_1), heartbeat (A_2), SPO2 (A_3), and stress level (A_4) while smartphone has been used to collect motion-based data e.g., surrounding temperature (A_5), level of gravity (A_6), rate of acceleration (A_7), and velocity (angular)- (A_8). The sampling rate is maintained between 1-5 Hz, while an observation period of 12 hours is extracted which mainly consist of active period of daily life of participants. The data is collected for 30 days of scheduled observation. Further, the data is synthetically processed using normalization and synchronization in order to obtain a labelled data which is then subjected to proposed deep learning method using artificial neural network. A sparse matrix of 4 layers ($n=4$) and 5 layers ($m=5$) has been developed that takes the input data leading to predicted outcome. The overall size of the data aggregated is approximately 1020.76 gigabytes which is further divided into three samples for performing investigation i.e., each sample-1, sample-2, and sample-3 consists of 340 gigabytes of data (both p_d and m_d). The assessment is basically carried out for all the four classes of mental illness, where we specifically emphasize that bipolar disorder type-I is aggressive and needed more attention. However, such rule formation can always be amended based on applications. The primary model assessment is carried out towards accuracy test.

Table 1 highlights the accuracy outcomes obtained for classification analysis carried out between α_1 and α_4 while Table 2 highlights the outcome for classification of α_1 and both α_2 and $\alpha3$. Finally, Table 3 highlights outcome for classification of $\alpha1$ and $\alpha2$. The numerical outcomes existing various instances of outcomes with respect to F1-Score, false negative (FN), false positive (FP), and accuracy. The significance of this numerical analysis of the accuracy is that for every combination of p_d and m_d samples, the proposed scheme is able to yield a satisfactory accuracy score. A further comparative analysis is carried out with respect to existing predictive approaches of CNN, long short-term memory (LSTM) and reinforcement learning (RL). The comparison is carried out to access the effectiveness of second algorithm for analytical operation.

Table 1. Assessment of accuracy for primary classification

Category	Dataset	F1-score	FN	FP	Accuracy
A_7, A_5, A_8, A_4, A_1, A_3	Sample-1	90.6	6.9	12.5	92.3
	Sample-2	83.1	48.9	7.7	92.5
	Sample-3	95.3	45.2	3.5	98.4
	Average	89.6666667	33.66667	7.9	94.4
A_7, A_5, A_8, A_4, A_1	Sample-1	90.5	5.5	24.1	91.6
	Sample-2	90.9	24.4	5.1	94.4
	Sample-3	88.1	43.1	3.6	98.6
	Average	89.8333333	24.33333	10.93333	94.86667
A_7, A_5, A_6, A_4, A_1, A_3	Sample-1	97.9	8.8	25.5	99.4
	Sample-2	77.4	56.8	6.1	93.7
	Sample-3	92.2	37.5	4.1	99.8
	Average	89.1666667	34.36667	11.9	97.63333

Table 2. Assessment of accuracy for secondary classification

Category	Dataset	F1-score	FN	FP	Accuracy
A_5, A_6, A_8, A_1	Sample-1	80.5	37.8	5.7	90.1
	Sample-2	93.8	32.8	5.6	91.6
	Sample-3	71.3	48.0	13.8	92.8
	Average	81.8666667	39.53333	8.366667	91.5
A_7, A_6, A_8, A_1	Sample-1	89.8	35.9	7.6	99.3
	Sample-2	94.1	36.8	2.1	92.3
	Sample-3	72.4	48.6	22.1	93.5
	Average	85.4333333	40.43333	10.6	95.03333

Table 3. Assessment of accuracy for ternary classification

Category	Dataset	F1-Score	FN	FP	Accuracy
$A_7, A_5, A_6, A_8, A_4, A_3, A_2$	Sample-1	92.1	3.9	58.2	87.2
	Sample-2	89.1	45.4	2.1	92.5
	Sample-3	94.9	36.2	3.2	90.9
	Average	92.0333333	28.5	21.16667	90.2
$A_5, A_6, A_8, A_4, A_1, A_3$	Sample-1	91.6	4.9	58.2	86.7
	Sample-2	80.1	45.3	1.1	92.7
	Sample-3	89.5	44.1	3.2	98.1
	Average	87.0666667	31.43333	20.83333	92.5

The comprehensive analysis of the predictive approaches is illustrated in Figure 4. The outcome shown in Figures 4(a) and 4(b) exhibits that propose analytical scheme excel much better accuracy and reduced response time in contrast to existing predictive scheme. The prime justification is as follows: although RL offers an optimal learning for its agent with better adaptability, yet it encounters complexity for assigning an appropriate reward thereby reducing the accuracy. RL also have a higher dependency of higher interactive set of environmental data in order to arrive at optimal policy for learning which causes highly increased response time.
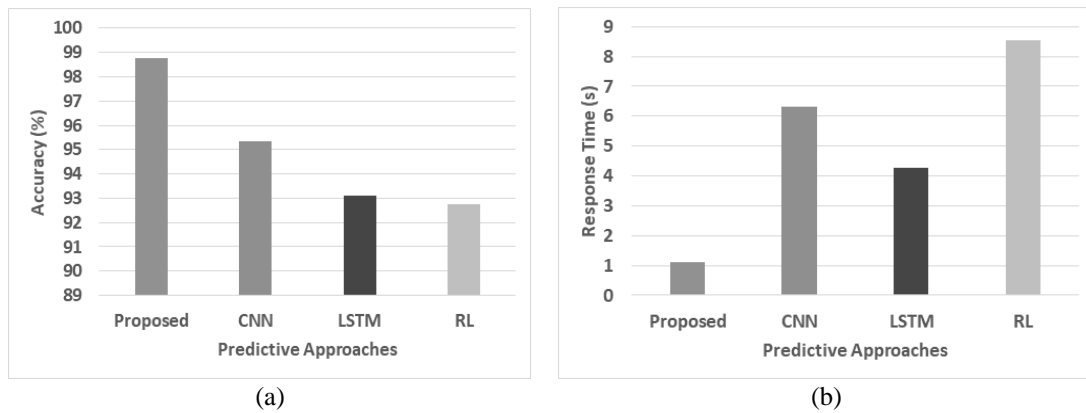

(a)	(b)

Figure 4. Comprehensive analysis of (a) accuracy and (b) response time

LSTM is found to be highly suitable for analyzing various form of data without any dependencies of truncation or padding; however, they are found to be highly complex from computational operation in contrast to architectures based on neural network. This leads to only minimal improvement in accuracy from RL and reduced response time in contrast to RL. CNN overcomes the problems of both RL and LSTM by offering an autonomous and hierarchical data representation causing improved accuracy compared to RL and LSTM. Another reason for better accuracy for CNN is also because of its ability to identify patterns irrespective of nature of signals. However, it is found incapable of modelling any dependencies of temporal and sequential order, whereas proposed testbed is a collection of such data, hence its response time is found to be quite higher compared to both RL and LSTM. On the other hand, the proposed scheme uses a deep neural network which is capable of autonomously learning logical representation of data using abstract features. Apart from this, proposed scheme also entitled usage of high-capacity parameters that can retain finer details causing significant rise of accuracy compared to CNN, LSTM, and RL.

The next part of comparative analysis deals with data transmission scheme introduced in the form of first algorithm in proposed system compared with frequently used standard of RPL protocol in IoT [48]. The performance analysis of the proposed work with RPL is illustrated in Figure 5. The outcomes exhibited in Figures 5(a) and 5(b) exhibits that proposed scheme offers lower delay and higher throughput in contrast to conventional RPL protocol. Following are the justification: RPL protocol is well-known for its capability to control resource consumption while considering data transmission using multipath apart from its beneficial aspect of scalable performance too. However, inspite of such high adaptability of RPL protocol, the network management implication for collecting the multimodal data from different places within a smart city in IoT, it introduces complexity in order to meet its objective function which is quite challenging to be aligned with proposed data aggregation environment constructed. Apart from this, proposed scheme calls for tracing the real-time signals from smartphones and smartwatches, where data arrival time is uncertain, it encounters an allocation problem towards configuring the network that causes increase in delay as well as reduction in throughput. However, proposed data transmission scheme autonomously select usage of both single and multihop communication on the basis of density concentration of user, which makes the schema highly flexible and more adaptable in contrast to conventional RPL scheme. Hence, the outcome showcase that proposed scheme offer a superior data transmission scheme for multimodal signal that can instantly propagate using both priority and regular channel. At the same time, adoption of deep neural network for diagnosis of bipolar disorder in proposed scheme is also proven to offer reliable accuracy outcome in contrast to existing predictive models.
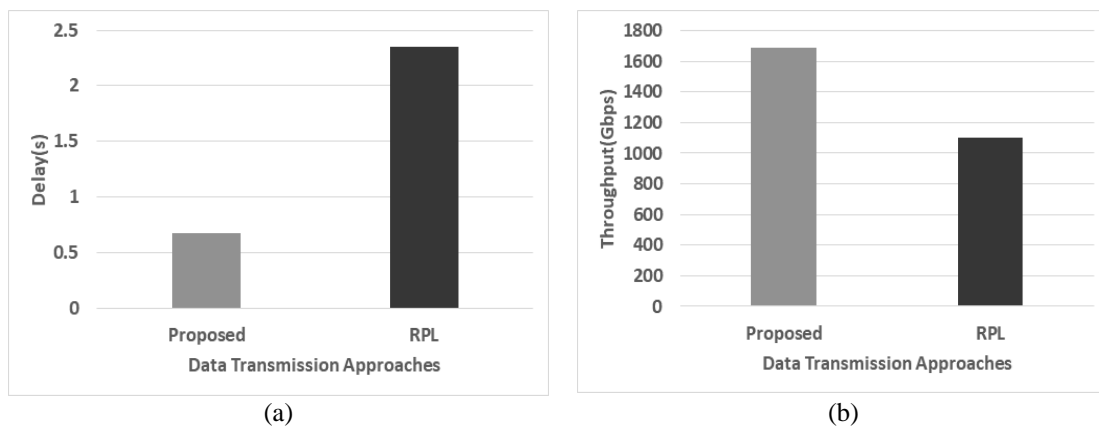

Figure 5. Performance analysis of (a) delay and (b) throughput

4. CONCLUSION

The proposed study has presented an integrated framework of transmission and analysis towards the direction of online diagnosis of bipolar disorder. The contribution as well as novelty attributes of the proposed study are as follows: i) a novel and simplified architecture towards IoT environment is designed where the patients are categorized on the basis of their density concentration (u_s, u_m, u_d) specific to location in smart city; ii) the scheme introduces two classes of information associated with bipolar disorder i.e., physiological data p_d and mobility-based data m_d aggregated from smartwatch and smartphones altogether. All the data from each origin are distinct in its type and hence forms a multimodal event data; iii) although both sensing devices seamlessly monitors data but not all the data are subjected to forwarding to gateway node. A clinical threshold-based scheme is used to identify the data when it matches with critical state of severity of bipolar disorder and then this data is forwarded and analyzed; iv) in order to offer a better traffic management, the scheme uses prioritized and regular channel of communication using single-multihop without affecting each other or any ongoing transmission; and v) simplified deep neural network is used for performing classification. The quantified outcomes are as follows: From analytical perspective, the proposed scheme exhibits approximately 38% of improved accuracy and 89% of reduced response time in contrast to existing predictive schemes. From routing perspective, proposed scheme exhibits approximately 70% of reduced delay and 43% of improved throughput in contrast to standard RPL protocol in IoT. The future work will continue towards the direction of investigating the impact of artifacts on the transmission scheme that has not been considered in current state of implementation. Further, a hybrid mode of learning scheme can be investigated towards higher accuracy targets on diagnosis bipolar disorder.

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