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POST-COVID REMOTE PATIENT MONITORING USING MEDICAL INTERNET OF THINGS AND MACHINE LEARNING ANALYTICS

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Abstract. The Covid-19 pandemic disturbed the smooth functioning of healthcare services throughout the world. New practices such as masking, social distancing and so on were followed to prevent the spread. Further, the severity of the problem increases for the elderly people and people having co-morbidities as proper medical care was not possible and as a result many deaths were recorded. Even for those patients who recovered from Covid could not get proper health monitoring in the Post-Covid phase as a result many deaths and severity in health conditions were reported after the Covid recovery i.e., the Post-Covid era. Technical interventions like the Internet of Things (IoT) based remote patient monitoring using Medical Internet of Things (M-IoT) wearables is one of the solutions that could help in the Post-Covid scenarios. The paper discusses a proposed framework where in a variety of IoT sensing devices along with ML algorithms are used for patient monitoring by utilizing aggregated data acquired from the registered Post-Covid patients. Thus, by using M-IoT along with Machine Learning (ML) approaches could help us in monitoring Post-Covid patients with co-morbidities for and immediate medical help.

Key words: Internet of Things, Machine Learning, Data analytics, Data Sensing, Data Aggregation, Covid, Post-Covid

AMS subject classifications. 68T05

1. Introduction. The Coronavirus pandemic has brought researchers across the globe from different domains to work together in-order to have better understanding and evaluation of the virus. According to W.H.O coronavirus is defined as an infec- tious virus which is caused by SARC-CoV-2 virus. People who are infected by the virus will experience mild to moderate respiratory illness and will recover without and sort of medical help but some however, will need proper medical care and any age group can get affected by it and may get severely ill or even they can die [1]. The pandemic initiated from Wuhan city, located in China in August 2019 and within few months, the whole world also got infected by the spread of Covid-19 virus. The abnormal situation created panic and chaos all over the world. Further, governments across the globe followed several protocols and imposed safety measures such as wearing masks, applying sanitizers, restricting unnecessary movements, lockdowns and so on. However, with time it is very clear that none of it has actually helped in the long term instead, the common people suffered a lot. The pandemic came with many negative health impacts resulting in serious mental and physiological concerns such as anxiety, depression, loneliness, cardiac attacks, arrhythmia and other health issues. The whole concept of normalcy that we used to live back in the days got totally changed and as a result the patient care and healthcare systems also got affected. The elderly people and others with existing morbidity are a major concern in situations like these.The general symptoms of Covid-19 are pneumonia, body ache, fever, rashes, diarrhoea, cough, fatigue, and loss of taste or smell, breathlessness and so on. Further, from the on-going research it has been found that 10-20 percent of Covid recovered patients experience post-Covid symptoms and these conditions are known as long Covid or post-Covid symptoms. The symptoms seen after recovery from Covid-19 includes fever, memory problem, difficulty in breathing, chest pain, anxiety, body ache, headache, tiredness, vomiting, nausea, organ damage, brain malfunctioning, brain fog, and so on. The duration in which the long Covid symptoms occur is still not clearly specified however, after 3-4

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Table 1.1: Similarity of Symptoms [7]

S.NO.	SYMPTOMS	COVID	POST-COVID
1	Fever	Yes	No
2	Cough	Yes	Yes
3	Sour throat	Yes	Yes
4	Runny nose	No	Yes
5	Head ache	Yes	No
6	Body ache	Yes	Yes
7	Chest pain	Yes	Yes
8	Loss of movement	No	Yes
9	Red eyes	Yes	No
10	Rashes	Yes	No
11	Diarrhea	Yes	No
12	Loss of taste	Yes	Yes
13	Loss of smell	Yes	Yes
14	Fatigue	Yes	Yes
15	Anxiety	Yes	Yes
16	Depression	Yes	Yes
17	B.P irregularity	Yes	Yes
18	Sugar level fluctuation	Yes	Yes
19	Pulse rate fluctuation	Yes	Yes
20	Breathlessness	Yes	Yes
21	Brain fog	No	Yes
22	Kidney infection	No	Yes
23	Blood thickening	No	Yes
24	Discoloration on fingers/ toes	Yes	No
25	Joints pain	No	Yes
26	Cardio vascular diseases	No	Yes

months of recovery from Covid, people may experience post-Covid symptoms [2] [3][4][5]. The availability of data for post-Covid scenarios are quite limited however, by looking at the symptoms in both the cases, it is evident that Covid and post-Covid symptoms possesses similarity. Thus, the datasets available for Covid can also work for post-Covid scenarios. The similarity of symptoms are illustrated in Table 1.1.

Hence, the best way to avoid post-Covid conditions is to take precautions, get vaccinated and follow SOP there by reducing the chance of getting Covid-19 in the first place itself. Thus, post Covid patient needs proper medical care and for that advanced technologies needs to be introduced such as medical IoT-based devices, ML and deep learning approaches along with healthcare data analytics.

IoT-based systems are a connected network of devices and sensors such as smart-phones, tablets, smart watches, EEC-ECG sensors and so on, to exchange the data over the internet. These devices are embedded with sensors that allows them to transmit the data. This method can be used for the patient monitoring scenarios for Covid and post Covid conditions. In medical healthcare, IoT devices plays an vital role in processing the patient's condition, consider an example where a patient's blood pressure level needs to be monitored so, for that wearable IoT-based device such as smart Blood pressure monitoring watch can be used for analysing the condition of the patient on a regular basis in real time. The collected data can be stored on the cloud and pre-processing of the same can be done over there therefore, the doctors can then easily monitor and track the patient's progress by simply using his smartphone. In critical situations like the pandemic people avoid going for regular check-up's as it is risky thus, IoT-based remote healthcare monitoring system can be used for keeping the health track of Covid and post-Covid patients. So, different IoT sensors and devices like the fitness bands, oximeter, ECG/EEG sensors, qardiocore and so on can be utilized for acquiring the data on a regular

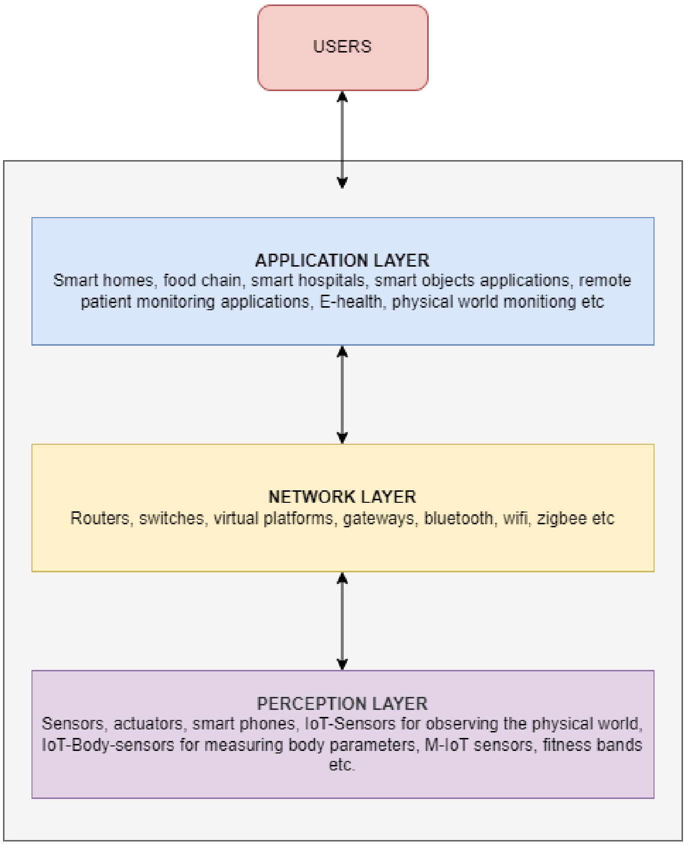

Fig. 1.1: General Architecture of IoT Technology

bases so that the monitoring of patients can be done while patient's stay at their respective homes. The general architecture of IoT-based technology consists of 3 layers i.e., the perception layer, the networks layer and the application layer as shown in Figure 1.1 [6].

The Perception layer acts as a physical layer where different sensors, devices, edge nodes etc. are connected in-order to collect the required data. Further, it helps in communicating with the surrounding and its various smart objects/ devices by detecting them. Once the data is gathered it is pushed to the next layer. The devices connected in the perception layer are sensors, actuators, Qr code and barcode readers, smart phones, portable pc's, surveillance camera etc. The Network layer analyses the sensory data acquired from the perception layer. Also, it helps in linking the smart object, network devices and servers. Further, it transmit the collected data by distributing and storing. The devices associated in the network layer are routers, gateways, hubs, switches, bridge, modules and so on. The Application layer acts as an interface between the user and the IoT-based system. It helps its users to access the data. Also, provides applications to its users by enabling them to use the functionalities of the sensors and devices. The different devices used at this layer are smart phone, pc's, smart watch, tablets and so on. Its applications can be seen in smart cities, hospitals, food chain supplies, etc.

ML approach is a method by which we can obtain hidden patterns and insights by using algorithms. The main objective of ML is to allow computer system to learn on its own by analyzing its environment without being explicitly programmed or hindrance by humans. Computers on its own are a very powerful machine which are good at calculations however, by applying ML we can make them intelligent predictors. To make the computers intelligent they need to go for training and for that datasets are used which helps the computer to gain experience and observe its environment, once the training of the model/ computer is done ML algorithms such as KNN, SVM, DC and so can be applied for accurate prediction. The basic work flow of the ML modelling

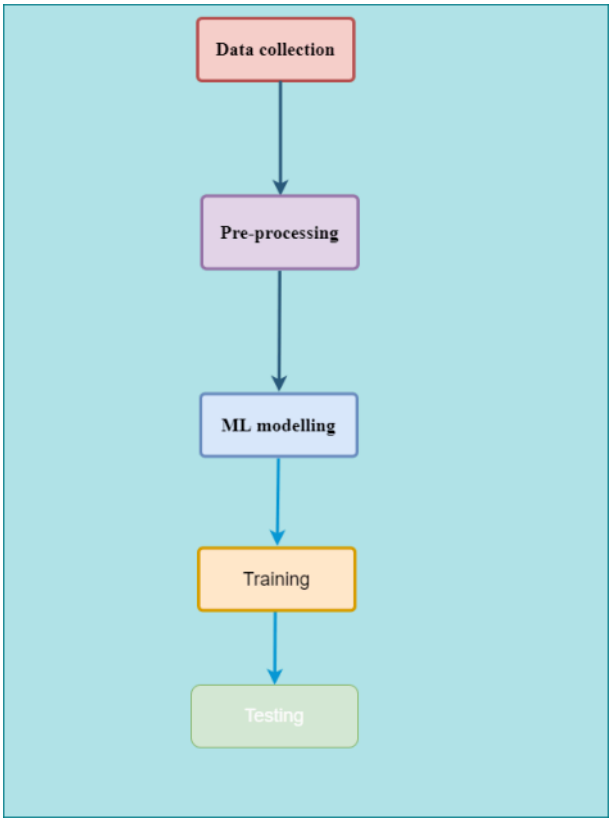

Fig. 1.2: Flow Diagram

is shown Figure 1.2.

The first step in the ML flow diagram is the data collection layer which is done in-order to gather all the related data of the proposed problem. There are a variety of methods used for data collection such as interviews, surveys, polls, observational, experimental and so on. Once the data is collected it is pre-processed in-order to have only the relevant data which is used for the modelling purposes. Once the model is built it is ready to go for training and testing purposes for providing accurate predictions. Further, ML algorithms are used for a no. of applications especially for diagnosis purposes in the healthcare sector. The conventional or traditional ML approaches like KNN, DC, SVM, Logistic Regression, Clustering approach, PCA etc. were used on its own for prediction however, the results obtained from these algorithm were not optimized therefore, the need for advanced technology came into existence. Ensemble learning is one of the powerful ML approach in which multiple ML algorithms are Integrated together such as regression, logistic regression, SVM, KNN, DC and so on in-order to form a stronger classifier for precise and accurate predictor machine/ model. The classifier has more predictive power, has lesser error rates and maximized accuracy on comparison with the traditional ML methods as discussed in [20]. The general layout of the ensemble learning classifier is shown in Figure 1.3.

At the bottom is the training dataset which consists of the dataset D that is divided into smaller partitions d1, d2, . . . , dn. These partitions of dataset are then used to train the classifiers or learners L1, L2, . . . , Ln at the second level. The learners makes classification and generates different outputs O1, O2, . . ., On respectively. The 3rd level is the combining decision which basically aggregates all the outputs and uses voting method to choose the best prediction. Finally the prediction P is generated. This advanced integrated approach can be incorporated for the analysis of Covid and post Covid cases along with IoT-based technology there by minimizing the spread of virus among the people. Thus, various IoT-based devices and sensors can be put on the human body for regular monitoring of the health status. The data provided by the sensing devices can be

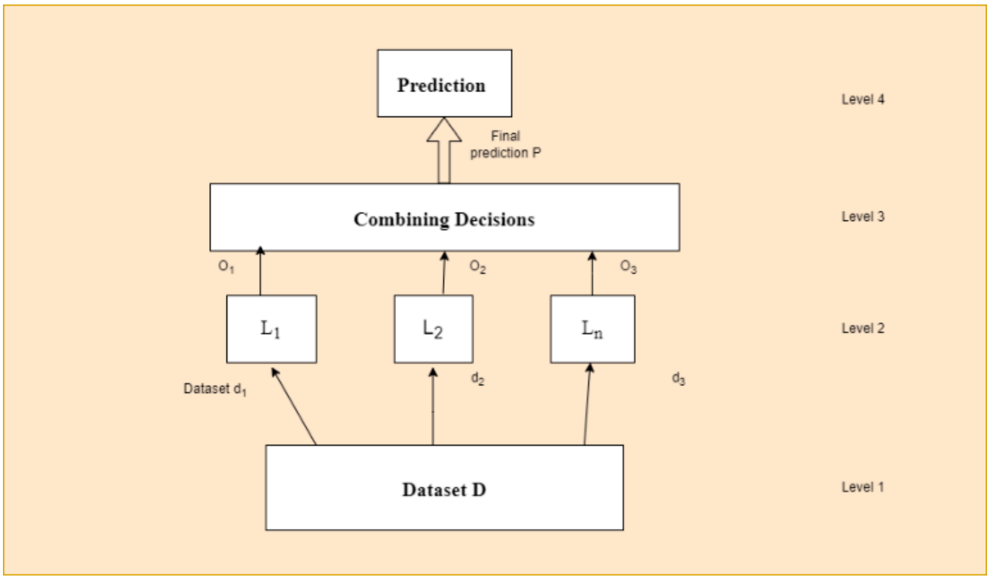

Fig. 1.3: General Layout of Ensemble Modelling

sent to the edge nodes where the aggregation of the gathered data can be done. Further, the aggregated data can be sent on to the cloud for pre- processing and modelling of the data in-order to generate reports for the doctors to have their expert recommendations. In this way the load on the medical staffs at hospitals can be seen reduced also leading to limited spread of the virus.

The organization of paper is: Section 2 discusses the literature survey, section 3 presents proposed IoT data models, section 4 implements the approaches for generation of data models, section 5 presents the real time setup and results, and section 6 gives conclusions.

2. Literature survey. There has been work done in IoT, ML, deep learning, cloud computing, cognitive systems, fog computing and Wearables for remote patient monitoring in Covid and post-Covid scenarios. These are discussed below.

2.1. IoT-Based technologies. The authors in [40] proposes an IoT-based sys- tem along with wireless sensor network architecture to monitor the quarantined pa- tients. Further, an urgent alarm system is also incorporated so that the healthcare professionals can get an urgent message via sms when there is any inconsistency in the patient's condition especially the elderly people needs more care. In the proposed architecture; Analog signals are received by the Arduino Uno which are sent by the sensors and transformed into digital format which is then processed by the micro- controller and the pre-processed data is then sent to the cloud so that healthcare professionals can access the data from anywhere. The authors in [43] proposes a re- mote smart home healthcare support system (ShHeS) in which patients are remotely monitored by the healthcare professionals and even patient's gets prescribed from the ease of their respective homes. The proposed mobile system interacts with the web application for better patient- doctor communication. Here, Sensors automatically captures the physiological parameters of the patents also, for service discover and context change of the environmental at home a hyperspace analogue to context (HAC) is added for accurate readings of the parameters. In this way, the new system reduces the hospital visits, queues and the cost of taking care of the patients at the hospitals.

An IoT-based Healthcare Assistance system is proposed in [32] for Covid-19 pa- tients. It's a survey based research paper in which they have integrated multiple IoT associated technologies like remote monitoring, robot based assistance, digital diag- nostic etc. which can be used for solving the problems faced during Covid-19 by the patients, health workers and doctors. They have also provided a wide range of do- mains in which existing health monitoring system have been developed which can be looked upon for solving the problems associated with the pandemic.

The authors in [34][13] proposes an IoT-based conceptual architecture that focuses on scalability, inter- operability, network dynamics, context discovery, reliability, and privacy issues faced in remote patient monitoring for the COVID-19 patients in hospitals and at home. Further, consent management module is also incorporated into the architecture that ensures data privacy and brings transparency to the patients. Also, an early-warning score method is used for checking and monitoring the hospitalized patients. An IoT- based System is proposed for safer movements in the pandemic using machine learning algorithms called SafeMobilit that integrates IoT, fog, and cloud solutions to monitor the social distancing between people and control the capacity in the spaces. Also, if any violation happens an alert message is generated and sent using IoT applications. Further, the fog node sends the information to the cloud server and displays the con- gestion sites in the environment. The results shows that SafeMobility has an accuracy of about 91 percent, hence the movement is detected in the indoor space as mentioned.[46]. In situations like the pandemic there is high risk of uncertainities therefore there is a need for awareness among the common people. Thus, a very impressive work done by the authors in [18] have proposed potential IoT and web technologies in the health sector for these scenarios.

2.2. ML approaches. The authors in [45]have proposed a method that classi- fies cough and is known as multi-criteria decision making (MCDM) method that uses ensemble learning techniques for COVID-19 cough classification. The Cambridge, Coswara, Virufy, and NoCoCo cough databases have been used for the training of the proposed method. Further, the proposed method incorporated TOPSIS. Soft ensemble and hard ensemble learning methods are used to identify the COVID-19 diagnostic model and machine learning techniques that give best results which are further used to classify the cough as COVID-19 or non-COVID-19 .Also, for the evaluation of the method entropy is used. A detailed study on machine learning, systems biology and bioinformatics is done thereby creating a disease model and host-microbe interaction disease network. The study can be utilized by clinicians and researchers to improve the prognosis, detection and treatment of post-COVID-19 mucormycosis that requires further evidence and testimonials in post-COVID-19 mucormycosis cases [16].The authors in [8] proposes an integrated method for the monitoring of Covid-19 by incorporating machine learning algorithms and IoT device. The model predicts the risk associated with COVID-19 pandemic by using ML algorithms such as Random forest (RF) and Naive Bayes (NB) classifier. For the data collection, IoT sensors are used and the accuracy associated with the RF and NB classifies are 97.The authors in [13] proposes a ML-based model for the prediction of anxiety during the Covid-19 pandemic in Saudi Arabia. The prediction models is developed by using Support Vector Machine (SVM) classifier and J48 Decision Tree algorithm. The results obtained for the early classification of two-class and three-class anxiety problems were exceptionally promising. The SVM gave 100 percent accuracy and the J48 Decision Tree gave 95.96 percent for the three-class problem and 93.50 percent for the two-class problem when predicting anxiety for earlier diagnosis and timely intervention using ten features.An Algorithm that helps in accessing the Covid-19 patients severity, needs and predict the length of their stay by using breathing frequency(BF) and oxygen sat- uration (SpO2) signals. BF and SpO2 signals of the confirmed Covid-19 patients who have been admitted in the ICU were used for the data collection that is then clustered using unsupervised ML method. The severity score S24 is utilised for representing patients severity; for the validity MS24 and maximum S24 score are used for evalu- ating the rates of intubation risk and long ICU stay. The proposed algorithm uses simple signals that efficiently visualizes the respiratory concerns of the Covid infected patients. The system includes 279 patients. The result obtained from unsupervised clustering for intubation recognition is about 87.8 percent [12]. In a similar manner the authors in [21] have proposed AI- based application for the diagnostic of diabetes retinopathy.

2.3. Deep Learning. The authors in [25] conducted a detailed review focussing the utility of AI in the domain of imaging for COVID-19 patient care. A systematic meta-analysis is done for technical merit and clinical relevance of the collected data. The main challenges and the gaps are discussed; thereby providing recommended solutions and remedies as well. The authors in [33] propose a deep learning-based framework by incorporating fuzzy logic that distinguishes between CXR images of pa- tients with Covid-19 infection and as well as patients who are not infected by covid-19 virus. The proposed model is known as CovNNet that is used for extracting relevant features from CXR images, which is then combined with fuzzy images that are gener- ated by a fuzzy edge detection algorithm. The proposed approach is validated using additional datasets.

Further, the experimental results shows promising results with an accuracy of about 81 percent. In [35] an in-depth study for imaging and medical image computing in COVID-19 diagnosis. The detailed study helps in providing tutorial for both clinicians and technologists, comprehensively review of the characteristics of COVID-19 as presented in medical images, inspect automated artificial intelligence- based approaches for COVID-19 diagnosis, and provide research limitations and the methods used to overcome them. By incorporating machine learning-based methods for the diagnosis of the disease will be helpful. Further, AI-based automated methods for COVID-19 diagnosis can provide promising results.

The authors in [28] presented aclassifier for COVID-19 detection which utilizes transfer learning for improving the performance and robustness of the DNN in vocal audio such as speed, cough and breathe. 10.29 h audio data is used that consists of four classes: noise, cough and sneeze. Further, the pre-trained COVID-19 audio classifiers use nested k-fold cross-validation. Thus, deep transfer learning method provides better vocal detection of Covid-19. The results obtained for cough, breath and speech are 0.982, 0.942 and 0.923 respectively. The authors in [26] described a model that uses artificial neural network (ANN) for the prediction of deaths and future daily cases due to COVID-19 in a generalized way so that it can fit the spread of different countries'. The proposed methodology predicts next ten days of the Covid- 19 spread that can be used for taking precautions and decreasing the spread. Also,87 percent accuracy is seen for predicting the number of cases and 86 percent accuracy is seen in predicting the mortality rate. In [9] an in-depth study of deep convolutional neural networks with the latest evelopments, protocols and applications is done to analyse the existing work. The rchitecture for COVID-19 prognosis is proposed with, limitations, outlooks and challenges for better modelling, design and training of the modules. Further, the study highlights the recent studies of the applications of deep CNN for, detection, screening, prognosis and classification, of COVID-19.

2.4. Cloud Computing. The study in [31] represents the characteristics, ap- plications and benefits of cloud computing and elaborates the improvement essential for cloud during COVID-19. The cloud computing helps the countries in handling the COVID 19, in commercial, educational, economic and health sectors. The results showed that cloud computing brings effectiveness during the epidemic. A framework that consists of wearable devices, clinical tests and hospital records for collecting Pa- tient data at the cloud infrastructure is proposed in [29]. For the Security at the cloud Audio-Steganography is used whereas for the authentication and faster transfer of data of a patient Near Field Communication (NFS is) used. Healthcare workers are performing their duty in critical situations like the pandemic the proposed automated framework will worker significantly by reducing the over load at hospitals.

The authors in [44] provided a model that transforms a modern hotel into a cloud- based virtual ward care centre that is integrated with cloud information system and social media which provides medical services just like hospitals. Also it provides an alternative option for patients to get quarantine. Routine ward rounds, measurements, recording of vital signs and medical consultation were done on social media platform to minimize the between staffs and patient. Therefore, Cloud-base information system are used for the Covid infected patients. An improved ML and cloud-based model is proposed to predict the threat of COVID-19 worldwide. Further, a case study in the paper illustrates the severity of CoV-2 spread worldwide. Using the proposed model statistically better predictions is obtained [14].An overview of cloud-based health- care system used for faster deployment in the organisations during the COVID-19 is proposed here. Detailed discussion on the consequences of cloud technologies and the issues related to data governance and privacy, data silos, unintended implications and data structures are done[42].

2.5. Cognitive Systems. A survey on Cognitive Computing (CC) is done in [17]. The paper consists of the challenges, solutions and future research directions as- sociated with it. Healthcare, cyber security, big data and IoT are the four fields where the application of the proposed work can be seen. A detailed study is carried out in which different applications areas for CC is discussed. The functionalities of cogni- tive dysfunction in patients after COVID-19 and the correlation between cognitive function and anxiety, depression, sleep, and olfactory function is done in [15]. A survey based research is carried for in which the applicability of Block chain technology along with in-depth discussion on the opportunities and challenges of the Cognitive Computing and Healthcare is done in [41].

2.6. Fog Computing. Fog assisted IoT-based framework is described for the protection and prevention from the coronavirus. The proposed framework predict COVID-19 infection by processing patient's health data. It is done by observing their symptoms thereby generating an emergency alert, medical reports, and precautions to the user, their guardians and as well as doctors and experts. It collects information from the hospitals and quarantine shelters through the patient IoT devices. Further, an alert message gets generated so that the government health agencies can take control to the outbreak of chronic illness and take quick actions accordingly [22]. The authors in [27]proposes an IoT, Fog computing, and Cloud computing based technologies for home hospitalization system. It allows the patients to recover and get treatment at their home, where patient health is monitored by the doctors and health workers to follow the hospitalization process and make recommendations to patients through monitoring units and mobile applications developed for this purpose.

A Health-care architecture is designed for processing, data collection, and trans- mission. It gives provides applicability of fog devices and gateways in Healthcare environment for current and future applications. The analysis for the cloud computing, IoT and fog computing is done to provide context-aware services to the users when required [37]. In [36] a cloud-fog-dew based monitoring Framework is proposed for Covid-19 management known as CONFRONT. The proposed model helps in di- agnosis and monitoring of the patients while they are in quarantine or home based treatments. To analyse large scale COVID-19 statistics data cloud servers are utilized because of its better scalability, computation and storage capabilities. It consists of heterogeneous sensors to realize the proposed model. Also, the Dew architecture has helped in improving the uptime of the proposed health care framework.

2.7. Wearables. The research in [24] is based on an in-depth survey, the pa- per explores virtualized care systems, wearable sensor devices, and real-time medical data analytics in COVID-19 patient health prediction. Analyses is performed and estimations are made for the COVID-19 patients. Descriptive statistics of compiled data from the completed surveys were calculated when appropriate. A predictive analysis is done in [23] on the downloaded dataset which are designed especially for COVID-19 quarantined patients. The wearable devices used on quarantined patients that provides the healthy and unhealthy patient data. The wearable device provides data of heart rate, SPO2, temperature, blood saturation, and blood pressure timely. The results of symptoms can identify the severity of the patient. In-depth study has analysed the risk of COVID-19 disease progression using random forest classifier algorithm.. The result has predicted the accuracy score of 99.26.

In [38] a proposed model is designed for detecting hidden signatures of Covid-19 by integrating biomedical sensors, and AI. The three types of biosensors: blood pres- sure biosensor, electrochemical biosensor, G-FET-based biosensor, and potentiometric biosensor are used for collecting the sensory data. The proposed model distinguishes between the severe and non-severe cases under the demographic features associated with it. The authors in [11] illustrated the utilization of different sensors used for improvement of the covid-19 disease control. The essential signs are measured and a details of the wearable systems used in emergencies such as epidemics is provided here. Implementation could help in better management and control and monitoring of the signs.

2.8. Wireless sensor network (WSN). A home health monitoring system is proposed in this research chapter to identify heart related risks and monitor oxygen level in a person by utilizing BSN simulator and energy performance of the network. This model helps to monitor and identify two types of condition in a person i.e., people with heart diseases and people who needs oxygen levels monitoring after recovery from the coronavirus disease [30].An IoT-based remote healthcare monitoring system is proposed in [39] that basically provides patient health conditions through Web browser. For simulation of the proposed framework Contiki OS with 6LoWPAN protocol stack and Cooja OS are used. The main focus of the work is to provide patient's vital parameters such as the ECG rate, glucose lever, oxygen level and so on through the Web browser; which is done by implementing CoAP protocol in Mozilla Firefox Web browserFor real-time regular health care monitoring a general three-tier omnipresent telemedicine scheme that is based on Wireless Sensor Network (WSN) is used to address healthcare related issues. Further, for the constant communication 3G/4G is incorporated with the wireless sensor network to increase the bandwidth that is calculated at TOA for proper communication [43].

3. Summary. A tabular summary of some of the papers in the literature review is presented in Table 3.1.

Table 3.1: Summary

References	Technology	Target population	Covid/Post-Covid
Sharma et.al[10]	IoT, Mobile Computing, Cloud Computing	Elderly people	Covid
Taiwo et.al [11]	IoT	General	Both
Verma et.al [16]	ML, Bioinformatics	General	Post-covid
Deepa et.al [17]	ML,Random Forest,Naïve Bayes,IoT	General	Covid
Boussen, et.al [20]	Unsupervised ML, clustering	Generic	covid
Born et.al [21]	AI, Data Analysis	General	Covid
Ieracitano et.al [22]	AI	General	Covid
Nabavi, et.al [23]	ML, AI	General	Covid
Pahar et.al [24]	Transfer learning,ML, Deep learning	General	Covid-19
Khanday et.al [26]	ML, Deep Learning.	General	Covid
Alhomdy et.al [27]	Cloud Computing	Generic	Covid
Moorthy.et.al [28]	Cloud computing, wearables.	Generic	Covid
Lim et.al [29]	Cloud Computing, Information system	General	Covid
Sreedevi et.al [32]	Cognitive computing, Big Data, IoT, Cyber Security.	Generic	Both
Delgado et.al [33]	Cognitive computing	Generic	Post-Covid
Singh et.al [35]	Fog, IoT.	Gardians, doctors	Both
Parker et.al [39]	Wearables	Generic	Covid
Hussain et.al [40]	Wearables, Data analytics, Random Forest.	Generic	Covid
Hemamalini et.al [41]	Bio Medical Sensors.wearables, AI	Generic	Covid
Rida et.al [45]	Wireless network.	Generic	Both

4. Proposed framework. The healthcare services and systems are still in the developing phase in India especially the rural areas have witness many challenges as proper medical facilities and infrastructure are not available to them. The coronavirus situation has further increased the level of difficulty in India, as a result rural areas have badly failed in tackling covid-19. The situation in urban India back in May 2021 was also very terrifying as they have failed in providing medical supplies, ventilators, treatments, oxygen cylinders and so on to its people thereby leading to countless deaths thus, we can imagine how worse the situation was in the rural areas. According to times of India around 52 percent of deaths were recorded in rural area itself in the month of May 2021 [47]. To overcome this issue we have proposed an IoT-Based remote patient monitoring system that helps in keeping the tract of the Covid and post-Covid patients while they stay at the ease of their homes. A variety of sensing devices are attached to the patients for regular monitoring along with lab testing's which provides the required data for the analysis purposes. Further, the gathered data is sent to the aggregate module where all the patient's medical data is combined in-order to form clusters which is then pushed to the cloud infrastructure for further processing and analysis. Also, medical expert module is also integrated in the cloud infrastructure layer that basically analysis and provide recommendations on the report generated by the modelling layer. The report along with the expert recommendation is sent to the patient as a feedback. The layout of the proposed framework consists of 4 different layers. At the bottom is the patient that uses IoT sensing devices for providing the data on regular basis also Lab testing results contribute in providing the data. Together the IoT sensing devices and lab testing results; form data monitoring layer that helps in gathering the required data of the respective patients. The data gathered is pushed to the aggregate module layer which helps in forming clusters of the collected data and further pushes it to the cloud layer. At the cloud the very first step is to pre- process the clusters by applying EDA method [10] [19]. Once the pre-processing is done, the data is sent to the ML modelling layer for applying classification algorithms in-order to classify the patients'

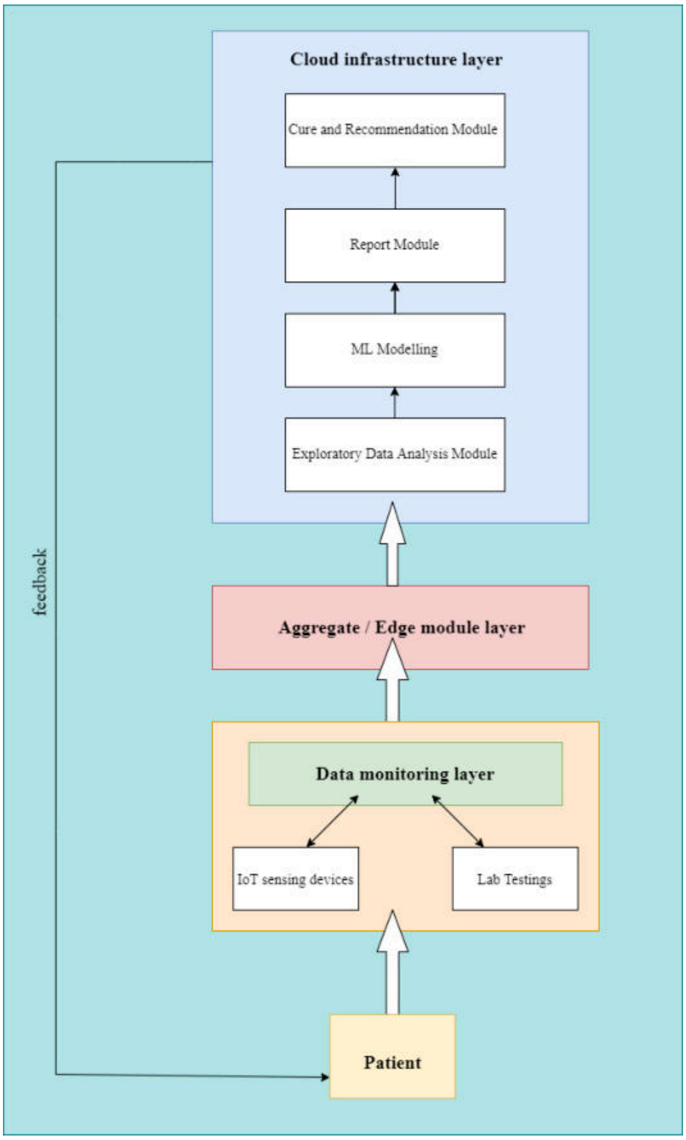

Fig. 4.1: Proposed Architecture Design

health status. The output generated is then transformed into documentation at the report module layer and the same is sent to the cure and recommendation module for expert opinions and recommendations. Once the processing is done the cloud sends the report along with the recommendations by the medical expert to the respective patient as a feedback.

5. System Design and Mathematical Modelling. The proposed Architecture has three functionality layer i.e, the data monitoring layer, the aggregate module layer and the cloud which are associated with each other i.e., the output of one layer is taken as an input on next layer and the process continues till the end as shown in Figure 4.1. At the bottom is the Data monitoring layer where the data is generated with the help of sensors and devices such as EEG sensor, ECG sensor, fitness bands etc. , and as well as with the results of lab tests such as the blood test, x-rays, urine test and so on. The data acquired helps in the monitoring purposes for the Covid and post-Covid patients. The data monitoring layer has 2 modules i.e.,the IoT sensing module and the lab testing module. The IoT sensing module consists of different sensing devices which helps in generating sensing data, hat is sent to the edge layer. Let I1 be the set of sensors described by 5 attributes or features of a patient P1.

Let I1 = P1, B1, O1, D1, T1 such that P1, B1, O1, D1, T1 representing pulse rate, blood pressure, oxygen level, diabetes and temperature respectively subject to constraints such that 60 $\leq$ P1 $\leq$ 100 per minute, 90/60 $\leq B1 \leq$ 120/80 mmHg, 92 $\leq$ O1 $\leq$ 100. Thus, at the Aggregate module layer the data generated at data monitoring layer gets pushed to the Edge layer where all the acquired medical data gets aggregated in-order to form clusters. There are two feasible scenarios of the system i.e., the Stationary IoT sensors-devices & Edge and the Dynamic IoT sensors-devices & Edges. At the Stationary IoT sensors-devices & Edge (at home/office) the location of all the sensors, devices and edge node is fixed and known. All the IoT sensors are directly associated with the particular edge device, providing sensory data DI1 to the edge. Let I1, I2, I3, ..., Iu be the set of stationary IoT sensor-devices attached to the patients at home or at office directing data DI1 to the edge node E. Therefore the regular monitoring of patients health can easily transmitted as the patient's location is fixed. At Dynamic IoT sensors-devices & Edge (from home to office and vice versa), both the IoT devices-sensors along with the edge nodes are moving. Therefore, any IoT sensor can get associated to any edge depending upon the nearness between them. When the patients are moving the monitoring of their health can be done via this scenario. To calculate the distance, let {(a11, b11), (a12, b12), . . ., (anm, bnm)} represent the positions of sensors {I11, I12, I13, . . ., Inm} respectively and let (ae1, be1), (ae2, be2), . . ., (aey, bey) denotes the positions of edge nodes/ devices {E1, E2, E3, . . ., Ey}. Thus, distance between sensors I11 and I12 :

$$d11 = \sqrt{(a11 - a12)^2 + (b11 - b12)^2}$$

The distance between the sensor I11 and edge node E1 :

$$D11 = \sqrt{(a11 - ae1)^2 + (b11 - be1)^2}$$

At the Cloud infrastructure layer, all the clusters formed at the aggregate module leyer is pushed to the cloud for further pre-processing and analysis of the same in order to have a better understanding and evaluation of the results. Here, the main objective is to evaluate the constrained which have been defined i.e. if I1 greater than T1 or L1 greater than T2 where, I1, L1 are the set of sensors and lab tests, and T1, T2 are their threshold values respectively.

After this, it connects to the doctors Doi and sends recommendations along with the report to the patient as a feedback. The cloud infrastructure consists of four different modules performing their respective functionalities. At the bottom is the Exploratory data analysis module (EDA) that is used for analysing the aggregated data values pushed by the edge layer. It is basically a collection of multiple methods which are used for understanding the variables, clean the data and visualize the data before developing the model for better understanding and evaluation. It aims to fetch hidden patterns, trends, associations, relationships present within the data. Thus EDA process helps to process raw data in-order to get meaningful insights allowing the developer to comprehend the data before making any assumptions. The EDA module has further three components:

- *Understand the variable:* For understanding the variables the first step involved is to import all the necessary libraries and load the datasets for shaping and applying mathematical functions to comprehend the variables and other constraints.
- *Clean the data:* It is one of the most important component used for removing redundant values, null values, removing outliers, fixing over or under fitting, fixing missing values, applying feature selection and feature engineering methods to obtain the relevant data on which ML approaches can be applied.
- *Analyse the relationship:* Visualization helps in analyzing the data by using visualisation techniques such as correlation matrix and graphical representations of the data points helps in better identifying the relationships between the values.

Once the data is pre-processed by eliminating the null values, redundant values and so on by applying EDA method, it is ready to go for ML modelling. So, various ML and deep learning classification algorithms are applied on the data at the ML modelling module for accurate prediction. Classification algorithm is a type of supervised learning method in which the data is classified into distinct categories of output. In the case for pandemic it classifies Covid and post Covid patient's condi- tion weather the person falls under the normal, severe or acute category. When the classification is complete and the model generates an output the same is pushed to the report module for documentation. When the prediction is made by the modelling module, the output data is documented into the report so that the same can be sent to the doctors for their expert examination and recommendation of the result. The cure and recommendation module basically helps in the evaluating the result report generated by the report module at the cloud. The doctor set Doi examine the report and provide recommendations if needed to the patient and the same is sent back to the patient along with the report as a feedback. Thus, we have C ← Doi, where C is the cloud and Doi = Do1, Do2, ..., Dox. Also, Do1 ← P1 and recommendations, R1 ← P1.

6. Post Covid Data Analysis. It is important to choose the correct data collection method as different tools are used for different research scenario. A dataset is a collection of related information that is gathered for a given problem. The dataset contains historical records or cases or observation and each case include numeric fea- tures that quantify a characteristic of an item. There are different methods available for collecting the data such as surveys, polls, experiments, reports and so on. In the case of Post-Covid patients the availability of the data is very limited and the research is still ongoing. We have seen similarity of symptoms in covid and post-covid cases however, exclusive datasets for Post-covid is a must therefore, in our research we have reached out directly to the PubMed and they have provided the required dataset. For the analysis purposes we have utilised RapidMiner studio tool which is a data science platform developed by Ralf Klinkenberg, Ingo Mierswa, and Simon Fischer at Technical University of Dortmund in 2001. It is a fully automated data science tool that provides an integrated environment for Machine Learning, Deep Learning, data analytics, text mining and predictive analytics [48]. The platform is used for commercial, business, educational, application development and research purposes as it provides features such as data processing, optimization, model validation and re- sults visualization. The complex analysis of the relevant features extracted from the dataset is discussed below.

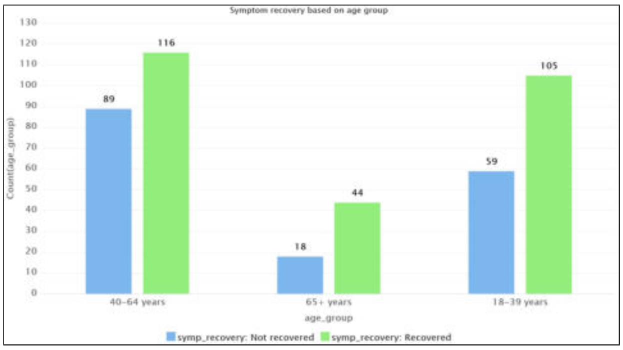

Fig. 6.1: Symptom recovery based on age group

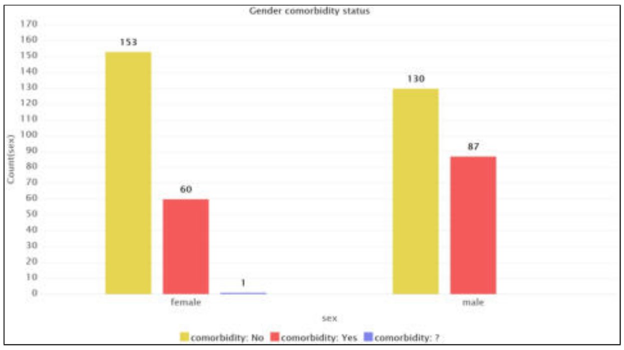

Fig. 6.2: Gender Comorbidity

Figure 6.1 represents the status of symptom recovery in different age groups. The x-axis shows the 3 age groups of the people as 18-39 years, 4-64 years and 65 and above. In the 18-39 age group 105 patients have recovered whereas 59 patients are not recovered, in 40-64 years age group 116 people have recovered whereas 89 people are still not recovered similarly in 65 and above age group 44 people have recovered and 18 people have not yet recovered.

Figure 6.2 represents the existing aliments in the gender. In the females 151 patients did not have any sign of comorbidity whereas 60 patients possesses signs of comorbidity. In a similar manner in the males 130 patients have no sign of comorbidity in them whereas 87 patients possesses comorbidity.

Figure 6.3 represents the status of respiratory issues on the three age groups. In the age group of 18-39 years 38.0 percent of respiratory issues are seen, in 40-64 years age group 48.28 percent of respiratory issue was recorded and lastly in 65 and above age group people possesses 13.8 percent of respiratory issues.

Figure 6.4 demonstrated the complication status in different age groups due to smoking. In the age group of 18-39 years 150 patients have no complications whereas 12 patients possesses complication. IN the age group of 40-64 years 158 patients have no sign of complications however 47 patients possesses complications. In a similar

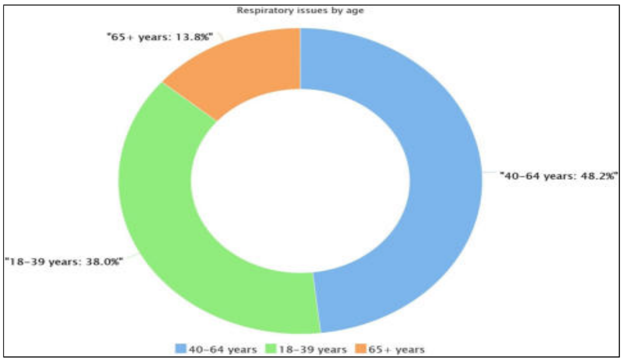

Fig. 6.3: Respiratory issues on age group

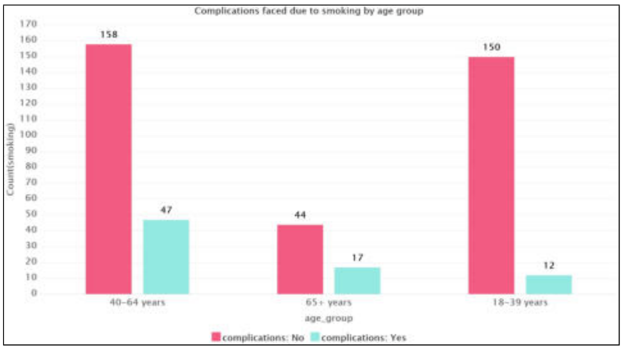

Fig. 6.4: Smoking complications on age

manner in the age group of 65 and above 44 patients shows no complications whereas 17 patients possesses complications.

Figure 6.5 shows Symptom recovery and complications in the infected patients. 126 patients have no recovery and has no complications either, 228 patients have re- covered and they also have no sign of complications in them. Whereas 40 patients have no recovery and also have complications. Even though, 37 patients have recovered however, possesses health complications.

Figure 6.6 illustrates the severity of symptoms in the infected patients and the complications related to it. The x-axis demonstrated the status complications in each of the severity group described as asymptomatic, mild to moderate and severe to very severe symptoms whereas the y axis shows the total count. In the asymptomatic group 36 patients have no sign of complications whereas 10 patients shows complications. In the mild to moderate symptom group 196 patients have no complications whereas 25 patients possesses complications. And lastly in the severe to very severe symptom group 122 patients have no sign of complications however, 42 patients possesses complications.

Figure 6.7 represents the presence of fatigue in patients according to their age group as 18-39 years, 40-64 years and 65 and above years of age groups. The x-axis shows the total number of patients facing fatigue and the y-axis shows the status of fatigue on age groups. In the 18-39 years of age group 59 patients have no sign of fatigue whereas 105 patients in the same group possesses fatigue. Similarly in the age group of 40 -64 years 100 patients have no sign of fatigue whereas 104 patients have fatigue. Lastly in 65 and above age group 34 patients show no sign of fatigue whereas 24 patients do have fatigue.

Figure 6.8 shows the presence of depression among males and females. The x- axis represents the categories of gender as male and female that shows the status of depression among them as no depression, mild to moderate depression and severe to very severe depression. And the y-axis shows the total number of patients in each of the categories. In the female group 149 patients have no depression, 50 possesses mild to moderate whereas 12 shows severe to very severe depression. In a similar manner in the male group 168 patients have no depression, 35 patients shows mild to moderate sign of depression and 14 patients falls under severe to very severe depression.

Figure 6.9 represents the presence of stress on the infected patients and their recovery. The x-axis shows the status of stress as mild to moderate, no stress, severe to very severe stress and the recovery associated with it. The y-axis shows the total count in each category. In the no stress group 80 patients are not recovered however 277 patients have fully recovered and are at the normal health status. Similarly in the mild to moderate stress group 20 patients have no sign of recovery whereas 31 patients have recovered back to normal. In the severe to very severe group 10 patient's show no sign of recovery and 7 patients have normal health status.

7. Discussion. The Post-Covid patient care has become more important be- cause of the fact that many patients develop complications after their recovery from the Covid-19. There have been many deaths reported in the Post-Covid era due to one or multiple organ failure which can be attributed to the unnoticed and unmonitored patients after covid. Although, we have analysed only few parameters for the Post-Covid scenario in our

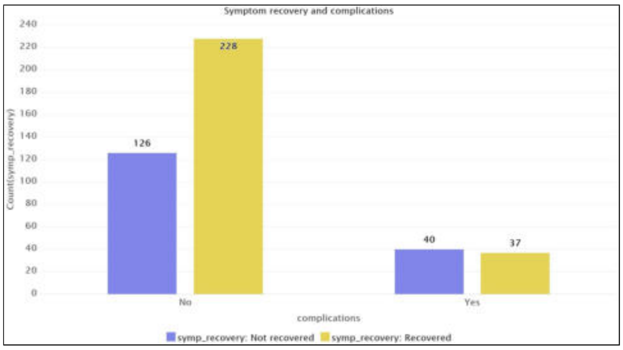

Fig. 6.5: Symptom recovery and complications

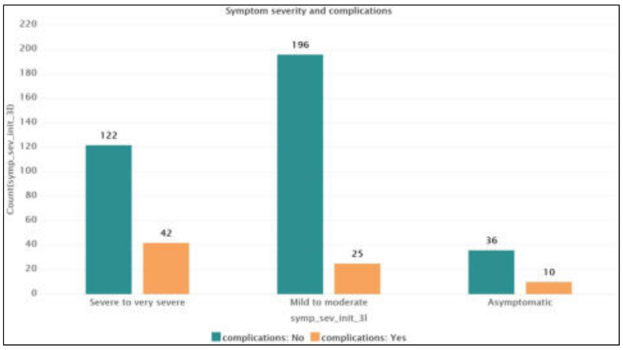

Fig. 6.6: Symptom severity and complications

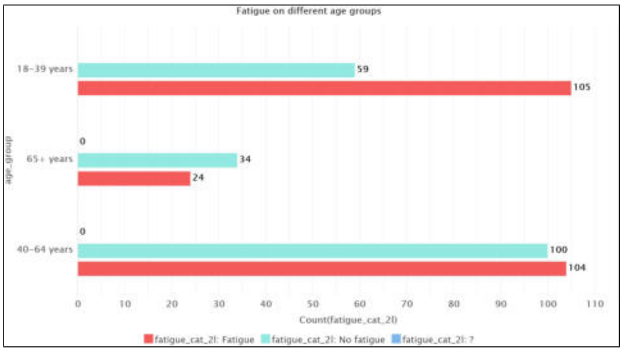

Fig. 6.7: Age group based fatigue

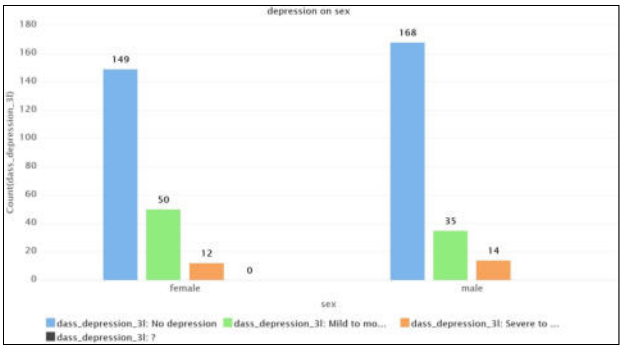

Fig. 6.8: Depression versus sex

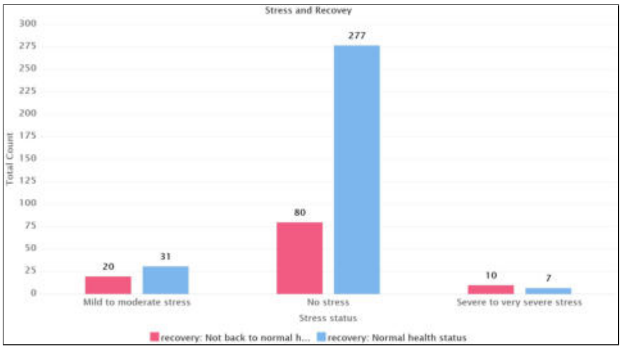

Fig. 6.9: Stress and recovery

data analysis but the trend in that the patients develop complications in the Post-Covid which is a matter of concern for all of us. It is therefore, a need of the hour to identify the parameters which should be monitored continuously in the Post-Covid era. The data has to be updated continuously and most importantly on regular basis. There should be data analysis to check the patients regularly and continuous if needed.

8. Conclusion. The medical IoT became the saviour in the Post-Covid and life situation. The remote health monitoring is possible through the M-IoT wearables but it also requires healthcare attention in real time to avoid any eventuality. The data aggregated from a patient remotely need to be analysed continuously and that is possible only through expert analysis and recommendations using the ML analytics. The proposed framework in the paper will help to offload a major portion of health monitoring for such patients from the overloaded medical staffs. Although the monitoring will be continuous However, the number of cases which require physical medical attention from the doctors and other medical staff will be lessen. The proposed work will be more required in the rural India where we have limited medical facilities as compared to the urban India.

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