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IOMT AND IODS IN HEALTH CARE FOR PULMONARY HEARTDISEASE DETECTION USING DEEP LEARNING TECHNIQUE

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Abstract
Living standards are largely determined by the availability of effective and high-quality medical care. In addition to accelerating disease detection and treatment, remote medical services provide the potential to reduce medical costs. A unified approach to connecting multiple devices, users, databases, etc. is possible with the Internet of Things (IoT). One form of IoT intended to support medical services is the Internet of Medical Things (IoMT). Many medical activities, including monitoring chronic diseases and diagnosing illnesses, can be completed remotely with the help of IoMT, which will save healthcare expenses and improve services. The Research work is based on using the Real World Data Set maintained by Kaggle. The data set is based on the thermal images of the patients captured from Drones using special- ized FLIR Camera. From data sets obtained, it has been observed there is increased rate in blood pressure, pulse rate, body temperature and respiratory rate within one month duration. From the obtained results it has been predicted that there is prob- ability of respiratory disease detection in patients moving inside and outside the hospital for 30 day's duration time period. In this research work confusion matrix is developed, which is based on Deep learning technique. Simple Neural Network is used as Machine Leaarning and Deep Learning technique. The predicted results are very helpful in identifying the status of patient suffering from respiratory dis- ease. This situation is also very dangerous for the healthy people inside the hospital especially patients care takers and doctors and paramedical staff. The effected pa- tient should immediately recommended for PCR Lab test. In case result found to be positive the patient is recommended to admit in hospital

INTRODUCTION

Nowadays people in the world face numerous public health difficulties relating to chronic diseases brought on by pathogens like Respiratory issues. Because of health issues and rising healthcare costs, everyone, notably the elderly and disabled, are urged to use computer-aided technologies to manage their health. As a network of interconnected devices, the Internet of Things (IoT) has opened up new possibilities for automation in various disciplines, including remote and intelligent healthcare [1]. WBANs, WSNs, and RFID are a few common technologies that make up the IoT. These technologies are used to send the collecteddata to the cloud, where it can be analyzed and extracted from the data for timely and accurate decision-making purposes. Health management systems can benefit from the IoT, which is increasingly being examined and used as a strong tool to make healthcare more personalized, proactive, and cost-effective. IoT applications in healthcare can be divided into three distinct categories mentioned as follows:

1. Tracing persons and other items (staff, medical teams, and patients)
2. Identification and verification of individuals
3. The system collects data automatically.

The IoTs can helps by avoiding hospital infections, managing emergencies, and providing post-discharge care, for example, by using WBAN technology, which monitors the health of the human body at all times [2]. The Internet of Things will transform devices, applications, and healthcare providers. Healthcare surroundings can be transformed by the Internet of Medical Things (IoMT) technology's ability to provide a personalized healthcare delivery approach via connected medical sensors or unique medical devices. Patients can get a wide range of telehealth services, including eldercare supervision, remote monitoring, consultations via the Internet, and computer-assisted rehabilitation, via the IoT in healthcare systems [3]. The words "IoMT" are sometimes used when discussing the integration of medical devices and applications with health care IT systems in an IoT context. Alternatively, a new sanitary system concept based on big data and the IoT allows for smarter administration of healthcare activities. Using big data analytics, it is now possible to perform prescriptive, autonomous, and predictive analyses of healthcare practices. Personalized healthcare can monitor patients remotely for diagnosis, early detection, and prevention. Chronic diseases like diabetes, obstructive pulmonary disease, cancer, arthritis, and heart disease are included.

1.1 Challenges in Modern Health care and IoT benefits

People with chronic illnesses, disease epidemics, high infant mortality, unsanitary living conditions, a lack of access to safe drinking water, and increasing pollution are all problems many countries around the world are grappling with when it comes to providing adequate healthcare to their aging populations [4].Hospital-centered healthcare practices confront several significant barriers and challenges, detailed in the following list:

The number of persons afflicted by illness or disability is rising. Doctors cannot spend much time with their patients. With less time to spend with patients, doctors have less insight into their daily routines, including their nutrition, sleep, exercise, and social connections. To properly diagnose and effectively treat patients, it is necessary to understand these aspects.

Rehabilitative activity, medicine, or dietary advice can be difficult for doctors to manage because they lack the proper training and resources. Non-compliance with therapy can raise a patient's healthcare costs, financial hardship, and the likelihood of subsequent hospitalization. The rise of the elderly - Medical facilities and resources will be needed to handle a bigger elderly population as the number of persons aged 60 and over grows by more than 200%, from 841 million in 2013 to more than 2 billion by 2050.

Urbanization - As predicted by the WHO, 70% of the world's population will be living in cities by 2015, necessitating the expansion of healthcare facilities in major cities to accommodate the influx. While major urban areas are more likely to be the center of illness epidemics, communicable diseases can spread swiftly in highly populated places.

1. The development of IoMT-enabled intelligent health monitoring systems using sensors and devices is one of the major contributions of this research study in the healthcare industry. The suggested approach makes it possible to monitor patients around-the-clock, giving medical professionals the ability to keep track of patient information and make wise judgements. Additionally, remote patient health monitoring helps lower readmission rates, which raises patient satisfaction and engagement levels.
2. The proposed framework allows the drones with cameras can help people in monitoring the

health status of people. The proposed system also allows the remote consultations with medical professionals.

2 RELATED WORK

2.1 Algorithms Applied to IoT Health Care: Machine Learning and Deep Learning

Many professions and fields are involved in healthcare research; scientists in medicine, microbiology, biomedical engineering, computer science, and Big Data analytics collaborate on related projects. Many gaps remain across these many specialties, and bridging these gaps will be a major technological challenge in establishing a healthcare system that is both unified and highly adaptive. IoT-based solutions are the most efficient means of developing this framework. Advances in the Internet of Things (IoT) have a major impact on healthcare. Microfluidic biochips and wearable biosensors, for example, can improve clinical diagnoses in a wide range of settings, from the laboratory to the hospital [5]. A doctor or other competent medical assistants were required to perform a physical inspection in the healthcare monitoring department to track a patient's progress during recovery. Waiting days for medical test results that had to be interpreted depending on the diagnosis was a frustrating process. IoT and AI-based gadgets that employ continuous monitoring to help detect disease and warn caregivers or doctors through an alert. They are based on artificial intelligence [6]. A Decision Support System (DSS) can use these gadgets to assist in decision-making (DSS). Machine Learning (ML) and Deep Learning algorithms, more commonly referred to as "Machine Learning" and "Deep Learning," are used to train these machines, which are preconfigured and ready for use. Various optimization methods, for example, have been incorporated into ML algorithms to improve the efficiency of health care services (HCS) [7]. Maximizing the use of cloud resources is an important consideration in these machine learning models. When there is a significant amount of data but no prior understanding of how to proceed, we can use nonparametric models. Fog computing and real-time data transmissions raise the importance of IoT devices in healthcare by restricting the collaboration of different healthcare devices with quick response times. Since Deep Learning and Convolutional Neural Network (CNN) technologies may be used together, IoT devices no longer have to be limited by WBAN's accuracy, opening the door to significant advancements in healthcare [8]. Machine learning techniques like C4.5, C5.0, KNN, and CNN are used to find missing data.

2.1.1 C4.5 Model (Application)

The C4.5 classifier is explained for both standardized and unstandardized pregnancy datasets. There are separate training and testing datasets for the unstandardized classification classifier [9] . A total of 37 data samples are included in the training dataset, one for each possible combination of the parameter value, result, and risk level. There are 12 parametric values for each data sample in the testing dataset. However, no outcome or risk level correlates to the parametric value set of each data sample. The decision tree is constructed using a Machine learning model and an unstandardized dataset using the C4.5 classification

2.1.2 Linear Regression Model (Application)

Stakeholders who interface with health-based applications have enormous obstacles, as outlined by [10]. The author addresses resource and time constraints. Determining the best virtual machines (VMs) to run HCS applications on the cloud can help them run faster and more efficiently. According to PPSO (Parallel Particle Swarm Optimization) was utilized to discover the optimal potential mix of VMs (Virtual Machines) for HCS in a cloud setting []. A hybrid cloud-based methodology for predicting CKD (Chronic Kidney Disease) has been presented. NN (Neural Networks) and Linear Regression can be used to create this model. The prototype's efficiency was determined by comparing it to the most advanced method [10].

Linear Regression Model in Health care is 50% faster and more reliable than the existing advanced methods

2.1.3 KNN Model (K-Nearest Neighbor)

[11] devised a KNN classification-based algorithm solution. Several individuals from a training dataset are chosen together with some additional information to show the entire training dataset to address concerns with low efficiency and dependence on the value of nearest neighbors denoted by K. For the sake of eliminating the user's dependence on the optimal nearest neighbor value K parameter is selected. Each representative is chosen using an optimal but varying nearest neighbor value K can also be determined by the dataset. In tests on six publicly available datasets, the KNN model proved to be a competitive classification methodology. For the random datasets used in the Literature study, accuracy comparable to C5.0 is better by the KNN modeling technique. Classification has reached the value of 90.41% by using the best dataset related to KNN Model.

2.1.4 Convolutional Neural Network Model (Application)

A subset of machine learning techniques known as "deep learning" is being employed in various fields today [8]. Speech and visual object identification have been proven to be more accurate with this technology than with other methods of recognizing them. Numerous processing layers in deep learning models enable the learning of significant raw data properties without subject expertise. On the other hand, traditional machine learning algorithms often require a large degree of domain expertise to extract features before they can do classifications. Among Deep Neural Networks, CNN includes two-dimensional inputs such as movies and images. CNN is widely employed in the field of computer vision. Millions of photographs can be used to teach them about thousands of objects. The depth and width of the model can be varied to alter the CNN's ability to learn. CNN may also process one-dimensional signals, such as ECGs or audio signals, in addition to two-dimensional signals. Numerous layers of computer units perform diverse jobs in a well-known CNN architecture for image identification [12].

2.1.5 Deep Belief Network Model (Application)

[13] describes the DBN (Deep Belief Network). It's a directed acyclic graph with stochastic variables that keeps growing. Multiple layers are connected via a series of latent variables. Layers are interconnected, but the units aren't connected to any of them. As a result of this training, it can correctly classify its inputs. Because of the greedy learning technique used by DBNs, they can only learn "one layer at a time."

2.2 Drones in Healthcare

Healthcare systems have the potential to benefit greatly from drone technology. Healthcare delivery has long been hindered by the difficulty of reaching remote or hard-to-reach locations, but with the advent of drones, which many have dubbed a "leapfrog" technology, that is changing. Life-saving materials such as vaccines or blood packs can be delivered more quickly and efficiently by drones, which can also boost the availability of healthcare supplies, expertise, and procedures in remote rural areas [14]. Drones' ability to satisfy healthcare requirements has been the subject of numerous research worldwide, contributing to the lack of proof. The world's drone pilot programs in support of national healthcare agendas and plans have been concentrated in Sub-Saharan Africa [14].

There is still a long way to go before drones for medical purposes in North America become commonplace. Drone applications in healthcare are heavily discussed in academic literature, much of which is theoretical. UAV-related applications in North America's healthcare and other sectors were investigated by [15]. Additionally, this scoping review's primary goal is to:

1. Describe how drones are being employed in North America for healthcare objectives.
2. Compile Published descriptions of these applications knowledge base.
3. Identify the knowledge base's shortcomings. An overview of the use of drones in healthcare and healthcare-related applications in North America is presented, and research goals are identified.

Various data aggregation techniques offer higher aggregation ratios with improved efficiency. For

instance, compressed sensing can reconstruct 90% of missing data from only 10% of measurements. However, this technique requires a significant amount of memory and incurs a high computational cost. Likewise, most existing techniques are designed for higher energy nodes such as cluster heads, aggregators, and mobile sinks. As a result, these techniques are infeasible for the resource-constrained sensor nodes. Therefore, novel and lightweight data aggregation techniques are required that are feasible for the resource-starving nodes [16].
Possible future extensions of this work will be to evaluate and validate it using real hardware or its implementation in related industries to see whether it can achieve its design objectives [17].
Recent years, witnessed significant growth in IoV with a diverse range of novel and innovative applications. It will undoubtedly improve our lives by ensuring safety and efficiency in the current and futuristic transportation systems [18]. In a nutshell, the complex relationship between data aggregation and accuracy, data aggregation and security, and data aggregation and QoS should be examined to make data aggregation techniques more resilient, optimized, energy-efficient, and trustworthy in the years ahead [20].

2.2.1 Screening and Diagnosis
The collection of pulmonary disease samples enhanced the danger of exposure to healthcare workers. The use of collaborative robots to collect pharyngeal and nasopharyngeal samples for respiratory testing has been implemented to solve the problem. Such cutting-edge equipment eliminates risk, speeds up the process, and may even enhance testing capacity. Mobile robots equipped with thermal sensors and automated cameras have been used to conduct temperature checks at strategic exit and entry points in public spaces. Patients and visitors to hospitals and other areas in China are being monitored for body temperature by mobile robots with facial recognition software. This way, respiratory screening can be done more quickly while maintaining social distance and lowering the risk of near encounters. Collaborative robotics and virtual reality software has also trained healthcare personnel remotely [21]. There are 5G-powered police patrol robots in China that aid first-line police personnel in completing disease prevention checks, including checking temperatures and separating themselves socially [22] .

2.2.2 Disinfection
For the respiratory disease epidemic to be contained, the use of robots and drones was increased to a greater extent. Drones and robot-controlled ultraviolet disinfection must be used to disinfect contaminated objects and surfaces. Public venues, hospitals, and densely populated regions necessitate greater manual labor to disinfect these surfaces, which may raise the risk of exposure, cost, and mental health issues. Most developed countries like Europe, China, U.S., and Dubai have all used drones to disinfect big open spaces, healthcare institutions, and even entire cities [23].

2.2.3 Surveillance
Following and complying with governmental limitations and procedures becomes more difficult when the socioeconomic populace is burdened with them. Monitoring people's movements, enforcing social distance rules, social gatherings, violations of lockdown regulations, and undesired activities in public spaces that enhance risk exposure to society have all been accomplished by using drones [24] .

3 IoD FRAME WORK INTEGRATED WITH WBAN
The Proposed Figure 1 describes in detail the proposed IOT-based framework using Deep learning techniques [25]. The framework is divided into three layers namely tiers. Each tier has its specific functionality [26].

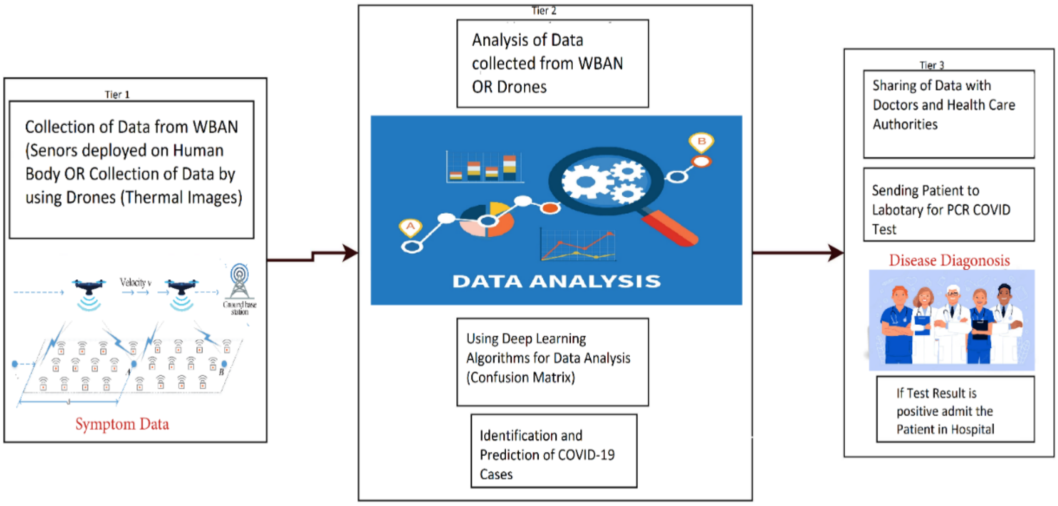

Figure 1: Three-Tier Proposed IoT-based Framework

Tier 1, is responsible for the Collection of the health status of people moving inside and outside the hospital environment. The data is collected in two ways Wearable sensors WBAN deployed on the human body and the data can also be collected using cameras installed on the drones to obtain the thermal images. The collected data will be related to the heartbeat, pulse rate, body temperature, and breathing status of human beings. The data from Tier 1 is transmitted into the computational server installed at Tier 2. The layers are responsible for performing Data Analysis using the Deep learning technique. We are using the Confusion matrix as a data analysis technique in this Tier [27]. Finally, on the prediction of pulmonary disease symptoms in people, the data is transferred to Tier 3. This tier is responsible for sharing the predicted data with doctors and healthcare authorities. Based on the predicted results the doctors will recommend the patient for a PCR test. Upon confirmation of a positive test, the patient is admitted to the hospital for treatment. In this Research work, we are using the Deep learning method named confusion matrix [27] in Table 1 mentioned as follows.

Table 1: Patient Data set obtained via thermal images.

True Positive (Tp)	False Negative (FN)
False Positive (Fp)	True Negative (TN)

A true positive value means that the people predicted pulmonary disease is having positive symptoms. Tue Negative value means that the people predicted pulmonary disease having negative symptoms. A false Negative value means that people do not predict pulmonary disease having negative symptoms. Finally false positive is an alarming situation that people who do not have pulmonary disease symptoms have positive symptoms.

4 EXPERIMENTAL SETUP

The data set for the experimentation had been obtained from the UCI Machine Learning Repository managed by the University of California, Irvine for pulmonary disease patient pre-conditions [28]. The total number of cases at hospitals in Australia was 566603. The Resource for the data set has been obtained live in the form of Microsoft CSV Excel Sheets [35]. We have picked the record of 47086 cases by random sampling of which has taken out 1014 cases as a convenient qualitative research sample.

The University of Waikato, Hamilton, New Zealand developed a Machine Learning tool (WEKA for ML) in the year 2022 for data preprocessing, classification, and visualization. We have used the WEKA tool for strong Analysis and decision-making based on our real-world data set in reliable diagnosis and intelligent decision-making by doctors and health care regularity authorities [29].

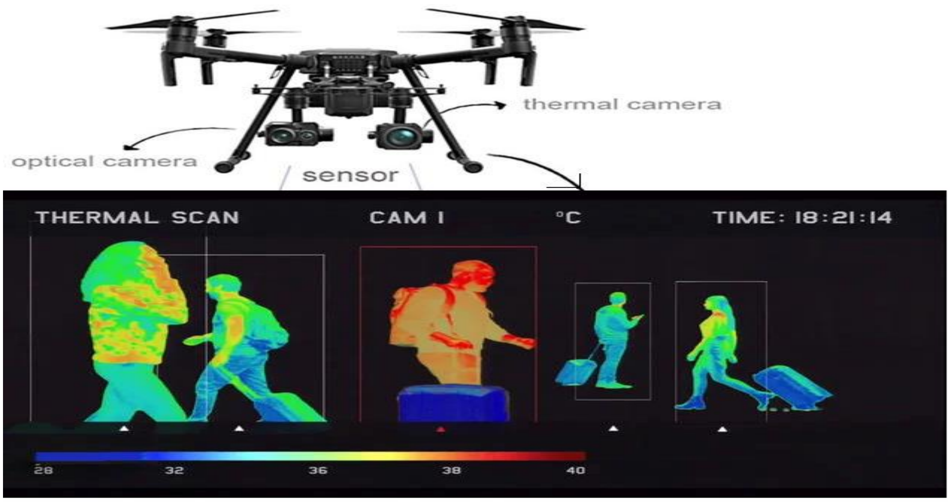

Figure 2: Drone Thermal images of the people

Figure 2 describes the Drone Thermal images of patients [30] obtained from the people. The observations which we obtained from Thermal images are based on blood pressure, body temperature, pulse rate, respiratory rate, etc [40].

4.1 Data Set Extraction

The following data set in Table 2 had been obtained from the Thermal images of patients and healthy people moving inside and outside the hospital environment. The National Engineering Company Machinery (NEC) Displays machine installed at the hospital is capable to extract the related parameters from the thermal images taken by drones [41].

Table 2: Patient Data set obtained via thermal images.

Sr. No	Country	Age (years)	Gender	Symptoms	Severity	Contact	Inside/outside the Hospital
1	China	0-9	Male	Fever	Mild	yes	Inside
2	Italy	19-20	Female	Tiredness	Moderate	No	Inside
3	Malaysia	20-24	Male	Dry cough	Severe	Don't-Know	Inside
4	Republic of Korea	25-29	Male	Sore throat	Moderate	yes	Inside
5	France	60+	Male	Breathing issue	Mild	Don't-Know	Inside
6	Spain	30-35	Female	Fever	Moderate	No	Inside
7	Germany	55-56	Female	Runny Nose	Mild	yes	Inside
8	Australia	60+	Female	Nasal congestion	Moderate	No	Inside
9	UAE	25-30	Male	Diarrhea	Moderate	Don't-Know	Inside
10	others	60+	Females	Fever	Mild	Don't-Know	Inside

The confusion matrix technique applied to ML technique. The ML technique which is used in this research work is Simple Neural Network [34]. The values for the confusion matrix are extracted from Table 1. The following confusion matrix values were obtained from the use of the Simple Neural Network (SNN) method in this study.

TP = 3
TN = 3
FP = 4
FN = 4

Accuracy is one of the most important parameter in calculating the performance of machine learning Algorithm [35]. Mathematically it can be computed as follows.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

..........................(1)

Precision is used to calculate the efficiency of supervised machine learning Algorithm [36]. Mathematically it can be computed as follows.

$$Precision = \frac{TP}{TP + FP}$$

....................................(2)

Recall is another method of calculating the efficiency of supervised machine learning Algorithm. Mathematically it can be computed as follows.

$$Recall = \frac{TP}{TP + FN}$$

....(3)

F1 score is used to calculate the efficiency of supervised machine learning Algorithm based on precision and recall values. Mathematically it can be computed as follows .

$$F1\text{-}score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$ ....(4)

Using ML and deep learning techniques, we had calculated the value of Accuracy equals to 0.42, Precision equals to 0.42, Recall equals to 0.42 and Fi score equals to 0.419 [37]. Approximately 0.90 value had been achieved by using these performance measures.

5 RESULTS AND DISCUSSION

Figure 8 describes about the graphical representation of ML technique based on confusion matrix. A confusion matrix is a useful tool in the healthcare industry for assessing how well diagnostic systems or machine learning models work, particularly in the areas of illness diagnosis, medical imaging, and patient risk assessment. It aids medical practitioners in determining how successfully a model separates people with a disease (positive cases) from those who do not (negative cases). The confusion matrix aids in calculating the advantages and disadvantages of using AI and machine learning to the medical field. Before models are applied in actual clinical settings, it guarantees that they are secure, dependable, and efficient.

The parameters values which we had calculated numerically are Accuracy, Precision, Recall and F1-Score [38]. In this study, the proposed deep learning-based framework leveraged thermal images obtained via drones to monitor vital parameters of individuals inside and around hospital environments. These parameters included body temperature, pulse rate, blood pressure, and respiratory rate, which are key indicators for identifying pulmonary and other respiratory conditions [42].

The experimental analysis used real-world data sourced from the UCI Machine Learning Repository, with preprocessing and analysis conducted. Out of a total of 47086 records, a qualitative sample of 1014 patient cases was selected for detailed analysis. The framework utilized a Simple Neural Network (SNN) and applied a confusion matrix to evaluate the prediction outcomes [43]. These results are regarded as promising for a real-time monitoring system using thermal imaging in an uncontrolled healthcare environment, notwithstanding the limited accuracy and precision (42%) that were attained. Despite obstacles such data noise, fluctuating patient behavior, and a variety of environmental variables, the deep learning approach has demonstrated promise in identifying patterns associated with respiratory disorders [44]. Important observations are highlighted by the graphical representations (Figures 3 to 8). When they arrived at hospitals, patients had high pulse rates and maximum body temperatures of about 100.8°C, which could indicate a fever or hypertension. While respiratory and pulse rates dramatically rose over the course of 30 days, systolic blood pressure showed significant fluctuation, raising concerns about the possibility of respiratory infections. With all measures clustering around 42%, Figure 8, which shows the confusion matrix-based ML performance, validates the balance between precision and recall.

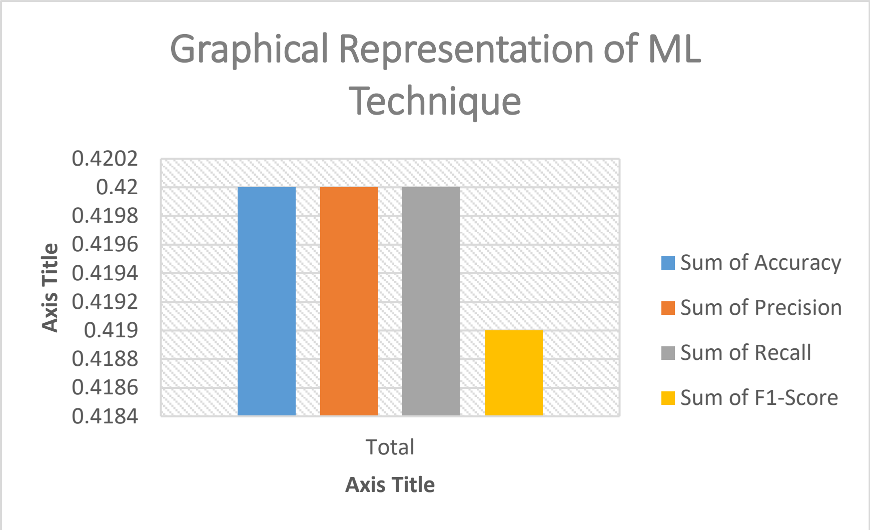

Figure 8: Graphical Representation of ML technique

From the graphical results it has been observed that the numerical values of Sum of accuracy, Sum of precision, and Sum of recall are approximately equal. This means that in our case the performance of supervised Machine learning algorithms [39] are predicted performance at 42% accuracy in case of this scenario. This novel is case of real time dataset obtained from Drones using Thermal images [40].

6. CONCLUSIONS AND FUTUREWORK

Overall, the architecture works well as a triage and early warning system. Although the systems predicted accuracy currently shows potential for development. Encourage health care providers to make well-informed diagnostic choices. Reduce the need for in-person screenings by using drone monitoring. Give people who are at risk real-time alerts to help with timely PCR testing and separation. A novel method for combining IoMT, drones, and deep learning to identify and treat respiratory diseases is provided by this study. This method integrated with WBAN in future will be essential for public health surveillance, hospital infection control, and pandemic response.

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