



Reduce the Spread Risk of COVID-19 based on Clinical Fusion Data and Monitoring System in Wireless Sensor Network

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Abstract

The expression “COVID-19” has been the fiercest but most trending Google search since it first appeared in November 2019. Due to advances in mobile technology and sensors, Healthcare systems based on the Internet of Things are conceivable. Instead of the traditional reactive healthcare systems, these new healthcare systems can be proactive and preventive. This paper suggested a framework for real-time suspect detection based on the Internet of Things. In the early phases of predicting COVID-19, the framework evaluates the existence of the virus by extracting health variables obtained in real-time from sensors and other IoT devices, in order to better understand the behavior of the virus by collecting symptom data of COVID-19. In this paper, four machine learning models (Random Forest, Decision Tree, K-Nearest Neural Network, and Artificial Neural Network) are proposed, these data and applied as a machine learning model to obtain high diagnostic accuracy, however, it is noted that there is a problem when collecting clinical fusion data that is scarce and unbalanced, so a dataset augmented by Generative Adversarial Network (GAN) was used. Several algorithms achieved high levels of accuracy (ACC), including Random Forest (99%), and Decision Tree (99%), K-Nearest Neighbour (98%), and Artificial Neural Network (99%). These results show the ability of GANs to generate data and their ability to provide relevant data to efficiently manage Covid-19 and reduce the risk of its spread through accurate diagnosis of patients and informing health authorities of suspected cases.

Keywords: COVID-19; Internet of Things (IoT); GAN; Machine learning; Clinical Fusion Data; Wireless Sensor network.

1. Introduction

Since it originated in the Chinese city of Wuhan in November 2019, COVID-19 has become a derogatory term around the world. The World Health Organization (WHO) has named the outbreak COVID-19. It began as a pandemic but eventually developed into a fatal epidemic[1]. With a 3.7% death rate in November 2021, COVID-19 confirmed case counts topped 257.46 million. Globally, COVID-19 has spread the menace and claimed 5.15 million lives. The Coronavirus family, which includes COVID-19, includes diseases ranging from the common cold to more severe conditions [2]. Since its onset in November 2019, COVID-19's chemical and physical characteristics have altered. New strains of COVID-19 are more susceptible and transmissible with a higher risk of infection [3]. On March 11, 2020, WHO declared the new COVID-19 pandemic. The majority of nations throughout the world have shut down all forms of travel, including air, train, and market commerce, in an effort to stem the spread of COVID-19. Numerous nations have also placed limitations or evacuated the city. The virus has destroyed the whole food chain, highlighting its vulnerability.

Due to frontier closures, business restrictions, and incarceration measures, the general small-scale businesses, street vendors, vegetable growers, and daily wagers were unable to access their local selling places, which disrupted national and international food supply networks and limited access to wholesome, secure, and varied meals [4]. In contrast, computer scientists are working to create models that can identify and stop infections. The conventional healthcare system is insufficient to

address the current worldwide predicament. Following regular operational practices and receiving immunity booster vaccinations are currently the only ways to prevent COVID-19 infection. The Internet of Things (IoT) is now integrated across all industries, enabling communication from anywhere at any time around the clock [5]. Advances and increases in mobile technology, such as sensors, smart devices, and other wearable devices mixed into the healthcare system, have a significant impact on our daily lives. IoT has sparked the creation of innovative, highly efficient devices for keeping tabs on people's health [6].

The combination of physical objects with communication tools that can exchange information across a network is known as the Internet of Things. The installed sensors are used to gather real-time health indicators that show how the patients are now feeling [7]. It is possible to locate COVID-19 suspects with the use of technology before the illness spreads. COVID-19-positive and COVID-19-suspected cases can be monitored and contained with the use of onboard mobile phone sensors and wireless sensor networks (WSN) [8],[9]. The combination of IoT with other upcoming technologies like machine learning and artificial intelligence may cause changes in the healthcare sector in the near future [10]. As a result, in response to the pandemic, machine learning (ML) and artificial intelligence (AI) have created new, possibly successful therapeutic options. AI and machine learning may be used to develop precise diagnostic techniques, find brand-new treatment targets, and recognize disease weaknesses. These potential applications require real-time patient monitoring and information synchronization, and the IoT is essential for both of these functions [11]. Foreseeing the impending coronavirus infection can be done in the future by utilizing AI and ML in IoT-based systems [12]. To further evaluate COVID-19, the IoT may be employed as a data source, and machine learning is used for data analytics [13]. To gain more understanding. IoT enables the creation of a centralized information system where all actions are electronically saved and accessible from any location at any time [14]. Numerous people lose their lives as a result of inadequate or inappropriate health information. Through installed or wearable sensors, IoT technology may immediately alert people to their health characteristics, The Internet of Things (IoT) technology can observe and record a person's regular actions and can produce the appropriate notifications if there is any serious health concern [15]. This study's main objective is to propose and evaluate a different strategy based on supervised machine learning for the precise real-time prediction of COVID-19. DT, RF, ANN, and K-Nearest Neighbour (KNN) were four ML models that were put into practice using a GAN-augmented dataset.

This work report is divided into five sections: Section II contains a summary of the most recent research literature. Smart Healthcare System for Tracking of COVID-19 in Section III, and the proposed prediction approach is described in Section IV. In part V, the results are analysed and discussed. Section VI concludes the analysis by outlining a potential follow-up initiative.

2. Related Work

In recent years, the technique of using IoT and artificial intelligence to reduce coronaviruses and predictions intensively. There are several studies on this topic. Several experiments with varied issues have been conducted in order to actualize domains and clarify the correlation between IoT and artificially intelligent. This section provides an overview of some of these studies. In [16] the authors constructed an accurate diabetes prediction framework using machine learning (ML)-based methods, a framework that they call the "intelligent diabetes mellitus prediction framework" (IDMPF), decision tree (DT), random forest (RF), and support vector machine (SVM) are three machine learning methods for COVID-19 prediction, The analysis of the data reveals that the recommended ML-based framework has an accuracy and root-mean-square error of 83%. In[17] the authors designed various supervised learning model for diagnosis using the machine learning models, three critical diseases suggested such as coronavirus, heart disease, and diabetes that run by android application and analysis in real-time, for their comparative study and logistic regression technique, the authors have made predictions. With the developments in ICTs that have made people's lives easier. In [18] Corona virus is an inflammatory disease caused by a new virus. The disease results in a respiratory infection (such as influenza). With symptoms such as fever, cold and cough, and in severe cases a problem with the respiratory system, and since the disease spreads rapidly from one person to another upon contact, it is difficult to predict the spread of COVID-

19disease, the researchers presented a model that may be useful in predicting the spread of COVID-19. Using the Kaggle data set, they used linear regression methods, multi-layer cognition, and vector autoregressive methods in order to optimally predict the epidemiology of the disease and its frequency. A comprehensive analysis was conducted of the most important healthcare technologies related to Industry 4.0, such as cloud and fog computing, Internet of Things and big data technologies. A vast array of material has been explored in order to study the fundamental technologies and uses of the Internet of Things in healthcare.

Another study by [19] The writers have talked about the potential for combining wireless technology and artificial intelligence to tackle pandemic conditions. The severity of COVID-19 patients may be predicted by the authors of this study using an ensemble machine learning model, or random forest method, which takes into account a number of characteristics. The suggested model has done well across practically all performance metrics, including recall, accuracy, and F1 score. The suggested method is contrasted with others like SVM, decision trees, logistic regression, and naive Bayes. In terms of performance metrics, the suggested approach outperforms every other algorithm. The proposed algorithm attained 94% accuracy, an F1 score of 0.86, 1.0 precision, and 0.75 recall. Ersin Elbasi, et al.[20], they put out a novel strategy that uses ML algorithms to keep an eye on the COVID-19 risk in public areas by measuring temperature, physical distance, and the presence of masks. By including more risk characteristics in the system, this model may also decide how to compute risk using machine learning methods. Through the use of IoT technology and machine learning algorithms, they have suggested a novel method for crowd monitoring that can identify safe and risky places. IoT sensors gather information for the feature vector from both interior and outdoor locations. For classification, grouping, and prediction, ML techniques are utilized. The accuracy of the decision tree approach is 94.50%, that of the naive Bayes classifier is 99.37%, and that of the random forest technique is 97.32% when using the same training and testing data. M. Hayder, et al.[21], The authors proposed a system for detecting COVID-19 in real time based on the Internet of Things, and they used artificial intelligence to predict COVID-19 and extract important features.

The oversampling technique was applied to unbalanced data and the algorithm for removing iterative features was used to select the most effective. Stability is indicated by the empirical prediction outcomes. With a maximum accuracy of 98% and an accuracy of 97%, the models' data compatibility was good, showing the model's high classification accuracy and usefulness for healthcare companies. HH, et al. [22], Mahmood The data are the symptoms that sensors and other Internet of Things devices have collected, and the researchers developed a framework that supports the Internet of Things in real time to recognize and anticipate COVID-19 symptoms in advanced stages. The data user, also known as the data gathering center, the analysis center, the diagnostic system, and the cloud system are the four primary components of the framework. Five machine learning techniques, including the support vector machine, decision tree, naive Bayes, logistic regression, and neural network, as well as performance indicators, were utilized to quickly identify COVID-19. Almost 95% accuracy, which was the greatest, was reached. Sajimon Abrahamin and Bilal Abdualgalil,[23] In order to predict COVID-19, the authors suggested machine learning algorithms based on clinical data. They made use of information from 600 patients and 10 test outcomes. They made use of performance metrics. Tenfold and holdout cross-validation methods were used to evaluate and validate the models' performance. In the holdout cross-validation strategy, the accuracy is 98.28%, F1-score 98.27%, accuracy 98.23%, recall 98.32%, and AUC is 98.32%; in the 10-fold cross-validation approach, the accuracy is 97.42%, F1-score 97.82%, accuracy 97.63%, recall 98.05%, and AUC is 92.66%. The studies' findings demonstrated that holdout cross-validation performed better than 10-fold cross-validation for all machine learning models. Karrar H, et al.[24] The researchers developed a system of Intelligent healthcare to predict the severity and manage critical tasks for COVID-19 patients a multi-agent system is suggested to prioritize patients according to the severity of the COVID-19 case and then give full therapy. On the one hand, a machine learning model is predicted to estimate the severity of COVID-19 disease. In this study, clinical data from 78 patients from a single hospital in Wasit Governorate, Iraq, including Internet Medical Sensors (IoMT) and electronic health record (EHR) data, were utilized to analyze the edge-to-cloud network. As the two main models for predicting risk, finite logistic regression (LR) and Random Forest (RF), respectively. Also, when compared to the most recent techniques, the RF model's prediction performance was strong and balanced, with 86% accuracy, 85.7% F-score, 87.2% accuracy, and 86% recall. Ahmed M. Dinar, et al.[25] The focus of the researchers was to develop a multiclass predictive system capable of dealing with three risk conditions (severe, moderate, and mild). the lymphocyte to CRP ratio (C-reactive protein blood test) and SpO2 the blood oxygen saturation level indicators was ranked and used as prediction system attributes. the SVM algorithm

as a machine learning model, the dataset of 78 patients with COVID-19 for the clinical dataset, the proposed model obtained an average accuracy of 82%, the applicable system early identifies three dangerous cases to reduce the number of deaths.

3. Smart Healthcare System for Tracking of COVID-19 based on clinical fusion data

Recently, the IoT has developed applications for smart healthcare systems. Wearable sensors are part of a smart healthcare framework that track a patient's or user's individual health state. Most notably, wearable innovation has become essential for regular health monitoring of users as well as remote patient monitoring. Wearable technology may minimize the number of times patients see doctors or health monitoring professionals. Also, it aids in the early detection of sickness, unsafe conditions, and smart hospital development. and study of drugs. It is important to investigate key developments that will improve the smart healthcare system. The user's health state is first researched using biological sensors such as blood pressure, patient priority, temperature, mobility, and how wearable devices are linked to the user's body to collect them. This section discusses the proposed smart healthcare system's framework, which is seen in Figure 1. There are two key data sources for the system. The Internet of Medical Things (IoMT) sensor data is the first one to be displayed on the left. Electronic health records are the second source of data (EHRs). An agent will be operating on each gateway whose responsibility it is to send the Bluetooth and Wi-Fi data of each patient's stream-detected data to the fog layer. The goal of the COVID-19 severity prediction model is to estimate the risk disease for patients based on the collected data. the following crucial processes are included in this engine: The initial three processes include information fusion, pre-processing, and a machine learning model based on the COVID-19 severity forecast. The recommended fusion approach is utilized in the first step to fuse the retrieved features from structured and unstructured data. The following stage involves pre-processing the data using information mining techniques. this stage also includes methodologies for meaningful feature selection and data standardization. In order to create the final prediction of patient severity, the pre-processed data is transferred to an ML classifier that has been trained on a COVID-19 dataset in the third step. The activities will be assigned (prioritized) by a (4) multi-agent system depending on their relevance after the phases of data preparation, prediction, and diagnosis. The intensive care unit will be allocated to the patient. Patients with a moderate level of criticality will be urged to undergo ongoing observation. In the most recent instance, when the patient is just somewhat critical, this will be suggested for more inspection. When all fog nodes are occupied and no resources are available, stream-detected tasks are processed by cloud datacenters, and patient history records are updated.

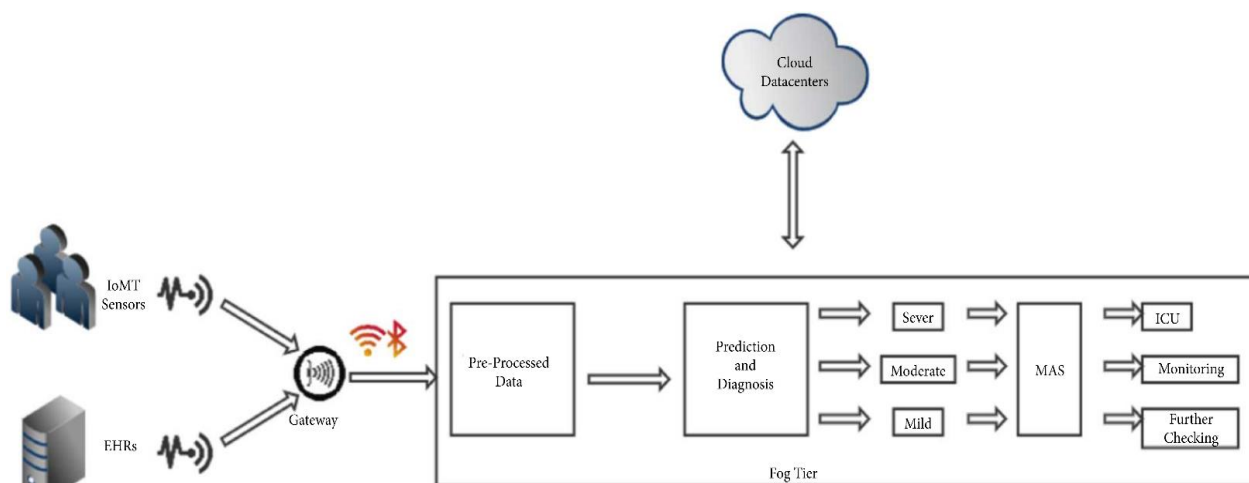


Figure 1: Smart Healthcare System for Tracking of COVID-19 based on clinical fusion data [24]

4. METHODOLOGY of prediction

In this work, the proposed approach goes through four steps as show Figure 2: The first step was the data gathering and analysis. Then, the GAN framework is proposed to generate synthetic data to augment the dataset. The third step was the pre-processing phase to hand missing values and standardize the dataset. The ML models were then implemented for binary classification. After the training phase using the generated dataset, the proposed models predict the COVID-19 patients. Models results then analysed and compared using the evaluation metrics.

A. Dataset

This study made use of the COVID-19 dataset from [26]. The data file is a tabular data set in CSV format with 78 rows and 29 columns. The COVID-19 data collection includes the following characteristics: Patients Age, Male and Female Survival(1)/Death(0), White blood cell count, lymphocyte count, platelet count, creatinine (mol/L), urea (mmol/L), and hemoglobin (g/dL), as well as Flu-like symptoms, headaches, generalized weakness, stuffy nose, sneezing, sore throat, pleuritic chest discomfort, and diarrhea Temperature of body 1 (°C), Saturation in oximetry (%), Heart disease, diabetes disease, cancer, target, lost sense of taste (1/0), and sense of smell (1/0). The proposed model's inputs are the first 28 characteristics, and its output is the "Target" feature. Figure 3 shows that only 48% of the dataset samples are mild, while the remainder are severe and intermediate.

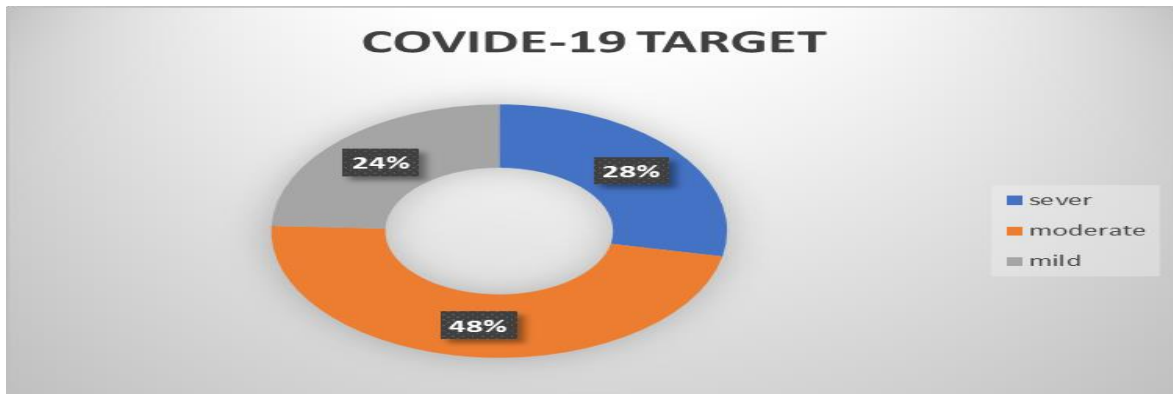


Figure 2: Pie Chart of Target Feature

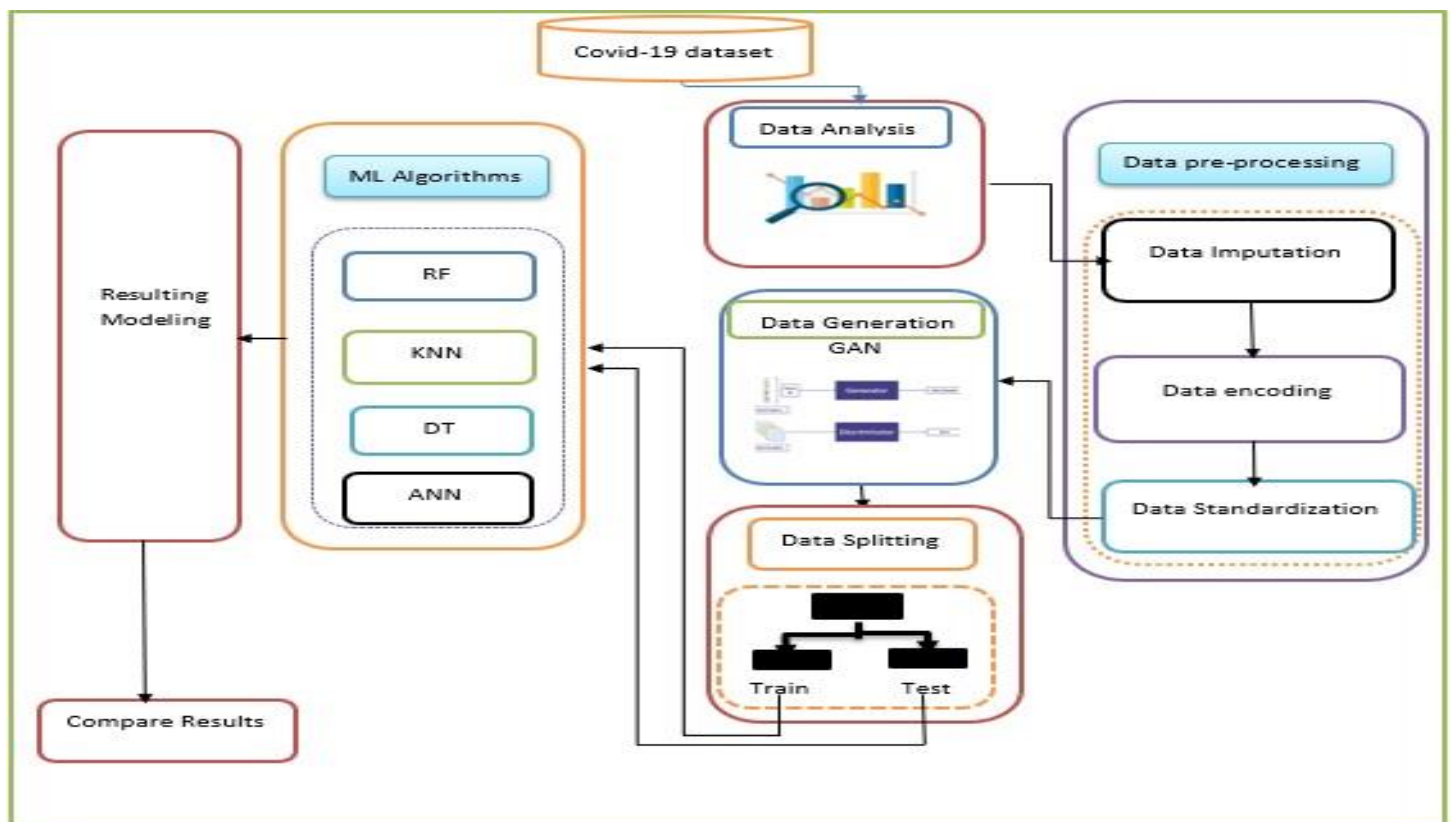


Figure 3: Covid-19 prediction proposed framework based on clinical fusion data

B. Data generation through GAN framework

In 2014 [27], GAN was released. To solve the problem of generative modeling, a supervised adversarial network was developed. GAN is composed of two multi-layer perceptrons (MLPs), a discriminator (Disc) and a generator (Gen). The Gen tries to deceive the Disc by generating false data by turning random noise into meaningful data samples, while the Disc judges if a data sample seems real or fake [28]. Together, the two models are being taught in real time, gradually enhancing their skills. The following settings were used to train the GAN model: the Adam optimizer, batch size=1, learning rate=5e-4, noise shape=32, input shape=28, and epochs=500. The dataset was expanded from 78 rows to 45000 rows after the data production stage .Figure 4 show the proposed GAN model.

. Generator: The Gen comprises of four thick (fully connected) layers, each with a growing number of units. ReLU activation is used in the first layer's 12 neurons. The second layer has 24 neurons, whereas the third layer contains 48 neurons. Moreover, ReLU serves as both of these layers' activation function.

Discriminator: The Disc is made up of a series of dense layers with ReLU activation functions and dropout layers to avoid overfitting. Each subsequent dense layer comprises 48 neurons, separated into two groups in the first dense layer. To determine if an input is real or fake, the output of the last dense layer is subjected to a sigmoid activation function.

Table 1: A table that includes the data augmentation process

Number of samples before using GAN			Number of samples after using GAN		
sever	moderate	mild	sever	moderate	mild
22	37	19	15000	15000	15000

C. Pre-processing

i) Data Imputation: The features (Haemoglobin (g/dL), White Blood Cell Count, Lymphocyte Count, Creatinine (mol/L), and Bod1 Temperature (°C)) are of the object type, must be converted to a numeric type for generalization and to facilitate their reading of the proposed model.

ii) Data encoding: Dealing with datasets in machine learning typically entails dealing with columns that have many labels in them. Both words and numbers can be used as these labels. The training data is frequently labeled in terms to make the data intelligible or in a format that is human-readable. To make labels machine-readable, they must be encoded as numbers. This process is known as labeling. A better decision may then be made on how those labels should be used by machine learning algorithms. For the structured dataset in supervised learning, it is a crucial pre-processing step.

iii) Data Standardization: StandardScaler is a pre-processing technique in ML that standardizes the feature values of a dataset to have a mean of zero and a standard deviation of one. The standardization process involves subtracting the mean of each feature from its values and then dividing by the standard deviation of the feature.

$$f'_j = (f_j - \mu_j) / \sigma_j \quad (1)$$

where f'_j is the standardized value for the j -th feature, f_j is the original value for the j -th feature, μ_j is the mean of the j -th feature, and σ_j is the standard deviation of the j -th feature.

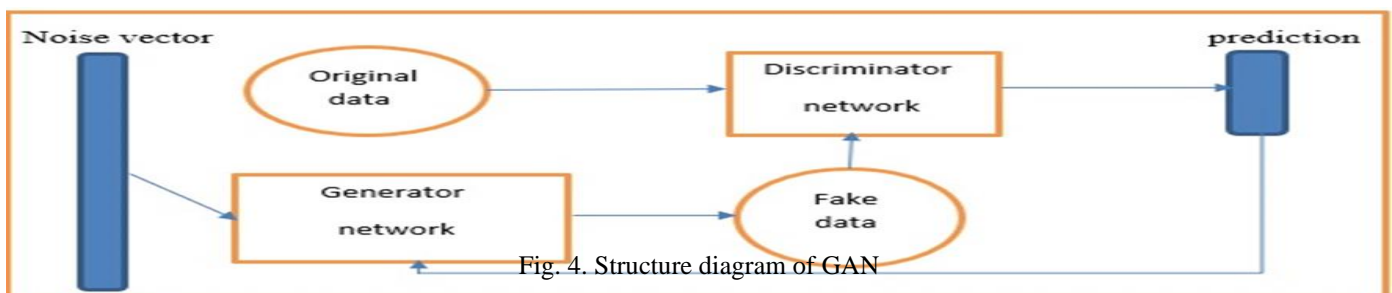


Fig. 4. Structure diagram of GAN

D. Proposed Classifiers

1) *Decision Trees Classifier*: A specific sort of ML algorithm called a DT is employed to categorize or forecast outcomes based on specified data properties. It is represented as a tree-like structure, in which the leaves denote the results, the interior nodes stand for qualities, and the branches serve as a guide for making decisions [28]. Based on that feature's capacity to lower entropy, the algorithm choose which feature to use to split the data. Based on the value of the selected characteristic, the data is then separated into subsets, and the procedure is repeated on each subset until the tree has grown to its maximum size.

2) *K-Nearest Neighbor Classifier* A case-based learning approach called kNN retains all of the training data for categorization. It cannot be used in many applications, such as dynamic web mining for a big repository, because it is a slow learning approach. One method to improve its efficiency is to choose some representatives to represent the complete training dataset for classification, which entails building an inductive learning model from the training dataset and using this model (representatives) for classification. Several modern methods, such decision trees and neural networks, were initially developed to build such models. One of the evaluation factors is the effectiveness of various algorithms. We are motivated to develop a model for KNN in order to increase its efficiency while maintaining the classification accuracy of the method because it is a straightforward but effective method for categorization and it is convincing as one of the most effective methods on the Reuters corpus of newswire stories.

3) *Random Forest Classifier*: DTs are learned in the RF model utilizing a sizable number of random selections of the training data [29] Averaging or majoritizing all of the tree forecasts yields the final result. Each tree makes its own prediction. The effectiveness of the model is increased and overfitting, which is commonly linked to single DTs, is reduced thanks to this method.

4) *Artificial Neural Network Classifier*: ANNs are computer algorithms that simulate biological effects to mimic how the human brain processes information [30]. An ANN is made up of neurons, which are stacked into layers [31]. Following receipt of the input data by the input layer and generation of the final prediction or judgment by the output layer. Layers that are concealed between the input and output layers analyze the data using weights and biases [32]. An ANN is trained using an optimization technique like stochastic gradient descent (SGD), which involves modifying the network's weights and biases to minimize the discrepancy between expected and actual outcomes [33]. This process continues until either the mistake is eliminated completely or the required number of training iterations has been reached. In order to prevent overfitting, in this work, ANN is built utilizing four dense layers with ReLu activation function and two dropout layers with a drop rate of 0.3. The dense layer's single output node and the fifth layer's sigmoid activation function result in the triple classification.

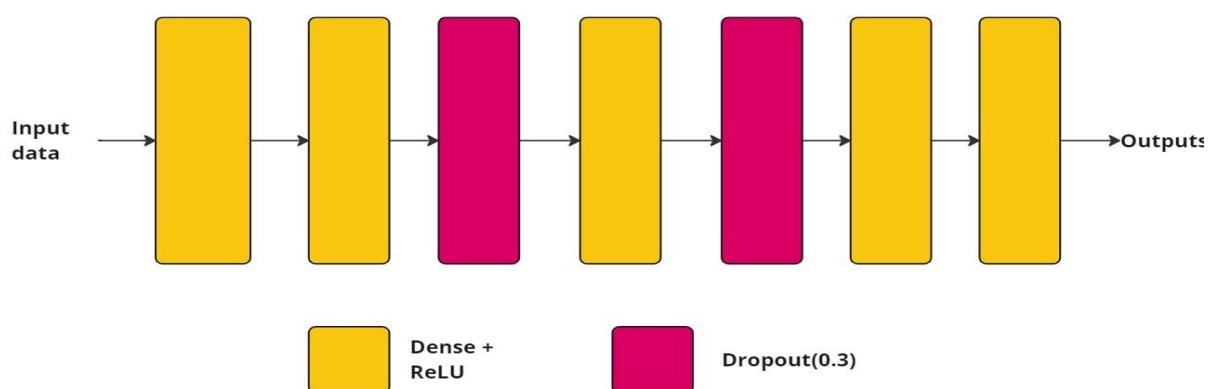


Figure 5: ANN Classifier architecture.

5. Results And Discussion

In this study, four classifiers were implemented to classify COVID-19 patients: RF, KNN, DT, and ANN. The results for evaluating these classifiers, in terms of ACC, PREC, REC and F1-Score (F-S) are presented in

Table 1. As can be seen, each classifier had a high accuracy classifier, with values ranging from 98% to 99%. This shows that the classifiers were generally successful in predicting COVID-19 patients. The RF and Decision Tree classifiers had the best ACC level among the classifiers. The ANN classifier performed well in terms of PREC, with values ranging from 0.98 to 1.00. A high score for PREC indicates that the ANN classifier was able to accurately predict COVID-19 patients since PREC is a measure of the percentage of positive predictions that are truly correct. The ANN classifier was also exceptionally good in terms of recall (REC), with scores ranging from 0.98 to 1.00. A high retrieval score indicates that the ANN classifier was able to accurately identify the majority of three cases, where retrieval measures the proportion of positive examples that were correctly identified (COVID-19 patients). The F-score is a harmonic mean for accuracy (PREC) and retrieval, and values ranging from 0.98 to 99 for all classifiers indicate that the classifiers have a balanced performance in terms of accuracy and retrieval. Figures 6, 7, 8 and 9 show the confusion matrix for RF, KNN, DT and ANN, respectively.

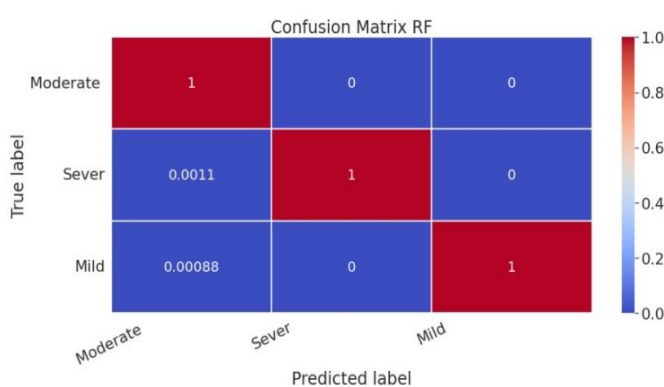


Figure 6: Random forest confusion matrix

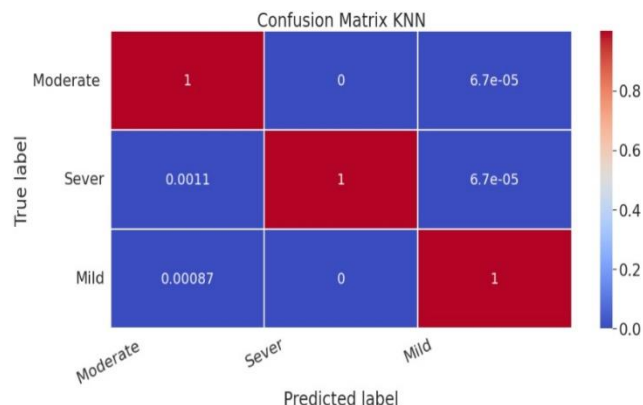
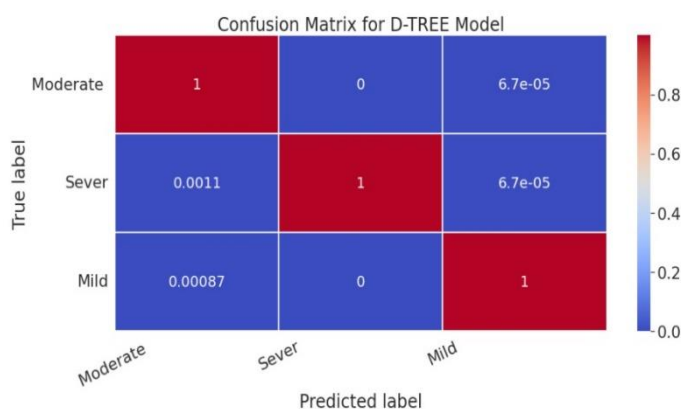


Figure 7: K-Nearest Neighbor confusion



matrix

Figure 8: Decision Tree confusion matrix

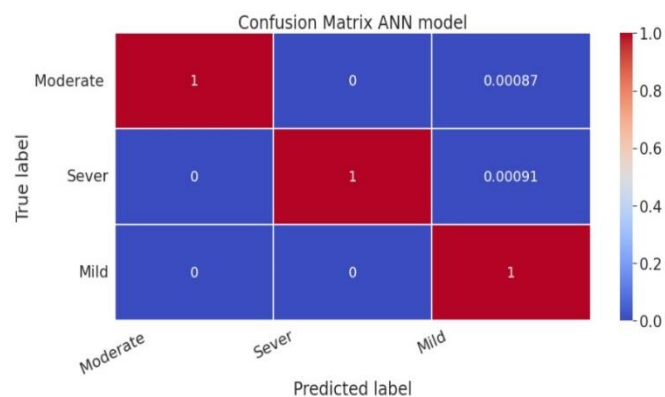


Figure 9: ANN confusion matrix

Table 2 : COVID-19 Results

Classifier	ACC	Covid-19	PREC	REC	F-S
RF	99%	Moderate	0.98	0.99	0.99
		Sever	0.99	0.98	0.99
		Mild	0.99	0.98	0.99

KNN	99%	Moderate	0.98	0.98	0.98
		Sever	0.98	0.98	0.98
		Mild	0.98	0.98	0.98
DT	99%	Moderate	0.99	0.99	0.99
		Sever	0.99	0.99	0.99
		Mild	0.99	0.99	0.99
ANN	99%	Moderate	0.98	1.00	0.99
		Sever	1.00	0.98	0.99
		Mild	1.00	0.98	0.99
SVM [26]	81%	-	-	-	-
DT [26]	75%	-	-	-	-

6. Conclusion And Future Work

Using intelligent systems to predict COVID-19 patients has produced encouraging results, with high accuracy levels being reported for a variety of methods, including RF, DT, KNN, and ANN. The findings show that these systems have the ability to deliver important data for efficient management and diagnosis of COVID-19 patients, eventually ensuring access to safe to safeguard healthy individuals and notify regulatory bodies. This work combines these systems with other technologies like remote sensing and the internet of things to get more detailed information about COVID-19. Real-world case studies must be conducted to show how these systems may be applied in diverse settings and to ascertain how they alter approaches to COVID-19 management and treatment. These results show the ability of GANs to generate data and their ability to provide relevant data to efficiently manage COVID-19 and reduce the risk of its spread through accurate diagnosis of patients and informing health authorities of suspected cases where the intensive care unit will be allocated to the patient if the severe case. Patients with a moderate level will be urged to undergo ongoing observation and will be suggested for more inspection. In the mild instance, lowering mortality rates.

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