Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

Tele-robotic recommendation framework using multi-dimensional medical datasets on COVID-19 classification

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ARTICLE INFO

ABSTRACT

The development of robotic partners to take care of daily human life has been expanded recently. Mobile robots have spread their presence within the public environment to assist people in a variety of problematic activities. Mobile Robots are developed with the underlying artificial intelligence technology. Adequate training is provided to the mobile robots under the classifications of supervised learning. The interaction of robots is very important to practice everything that is told to the robotic systems from domestic robots to high-risk work environments that threaten the health of the spinal cord, which focuses on robotic support during the COVID-19 epidemic. In the present research work, a mobile agent is trained using Computerized Tomography (CT) scan reports and X-rays under VGG-16 processing standards for classifying covid and non-covid patients. A hybrid model is designed using Deep Learning Network (DNN) and Convolutional Neural Network (CNN). CNN is trained using images collected using a camera and thermal camera with RGB values ranging from 0 to 255. The advantage of the proposed model in training the mobile agent is making use of CT scan and X-ray images and providing recommendations to the victim about the criticality of being affected by covid. In addition to that, the Machine Learning Algorithm like Decision Tree and Random Forest is constructed and achieved a classification accuracy of 95%. The proposed technique has efficiently provided a reliable recommendation system based on ReLu activation. The other evaluation parameters used to estimate the performance of the proposed model are precision, recall, F1-score. The proposed model achieves 0.84 Precision over the inception technique with 0.79 precision. The reason behind the improvement of accuracy in the present work is the filter used to extract the features.

1. Introduction

Corona Virus is the most threatening virus spread so far which has affected the entire world to a great extent. The virus effects are in ranges varying from mild to severe respiratory infection. Life is at stake for persons having a previous medical history and this type of virus creates severe damage to the persons who are already in treatment for some kind of diseases like lung diseases, heart-oriented issues,

diabetics (Haleem et al., 2020). Also, COVID–19 has pulled down the global economy massively. Many small scales to big businesses got affected due to this virus threat. Many of the industries have cut down their manufacturing and distributions are also greatly affected. Restrictions are imposed on various entities like public gatherings, traveling, organizing events and parties, the opening of educational institutions, organizing sports events (Tang et al., 2020). The spreading of this disease has to be controlled by ensuring and adhering to the instructions provided by the World Health Organization. The safety measures like regular washing of hands, wearing masks, maintaining self-hygiene, maintaining social distancing can keep the virus in control. In such a threatening scenario in order to save the health care sectors and the

community social workers who work in the COVID-prone zones, mobile robots can be used.

Mobile robots are the new age robots that are developed to lessen the daily chores and basic work like cleaning a room, tracking an object, alerting a security breach, monitoring (Ahmed and Patil, 2016), etc. All the possible measures that can be employed to avoid close contact are taken into consideration in the process of designing the mobile robot. Health care workers like doctors, medical assistants, social workers must be protected amidst their dedicated life-saving services provided to the community. Hence a mobile robot can greatly help this kind of service-minded people and prevent them by having close contact with the covid affected patients. Apart from the regular activities performed by the clinical robots, the proposed system has been planned to develop certain special activities like using digital thermometers and recording the body temperatures, maintaining outpatients records, identification of overcrowding in a particular zone, and providing an alert signal for immediate dispersal and so on. Not only in the field of health care sectors, but in various forums where social gathering should be controlled, automation to limit the number of people involved in task completion, the mobile robots sounds to be very effective. Henrik Christen, the director of the UC San Diego Contextual Robotics institute said that "Robots are designed by engineers for engineers ", which implied that robots are not easy to operate. This instills us to develop robots that are easier to operate and reduces the time spent in learning how to operate a robot to get a simple job done! Robots have played a salient role by serving their maximum capacity during this pandemic. It is sure to revolutionize the whole world by serving its purpose in situations like the current pandemic.

Different artificial intelligence algorithms are available to empower mobile robots to complete the assigned task effectively with minimal supervision. The platform developed for operating mobile robots can provide two or three degrees of freedom for their mobility. Several mathematical models are involved for their arms and wheels fixation. Kinematics is used for motion and its control. Mobile robots consist of the following components like sensors, actuators, and a control system. Mobile robots are applied in different sectors like navigations, mapping, localization, image processing, etc. Certain robots are designed and developed for industrial purposes where they are utilized in assembly, machine handling, and heavy materials handling and auditing (Rubio et al., 2019). Mobile robots in health care sectors have been used to perform various operations like cleaning the room, collecting clinical waste materials like used gloves, injections, using surgery masks, picking and placing the medical trays, and so on. Even in certain countries, medical mobile robots are used in assisting surgeries. The common architecture to extract data from CT scan and X-rays are presented in Fig. 1.

Deep Learning is a subset of Machine Learning interns a subset of Artificial Intelligence (AI). Where AI is a technique to mimic human behavior. The features of CT scan and X-ray reports are fed into Deep Neural Network (DNN). The input convolution layer splits the images into small chunks and features are extracted the weights associated with each neuron are used to estimate the important features from the images with the help of Bias. The activation function gives the output based on the input received from the hidden layers. The output layer finally produces the output in binary form. In our research whether the image is having covid-19 symptoms or not. The weights and biases at each hidden layer are continually adjusted to produce a well-trained deep learning network. The proposed system a hybrid model is engineered that is designed using Deep Learning Network (DNN) and Convolutional Neural Network (CNN). The constructed model is trained and tested using both CT scans and X-rays to detect the Covid-19 victims. The advantage of the proposed model in training the mobile agent is making use of CT scan and X-ray images and providing recommendations to the victim about the criticality of being affected by covid.
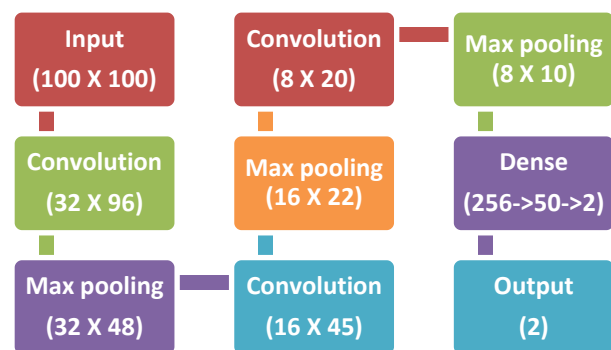

Fig. 1: Common architecture for both CT scan and X-rays reports

The organization of the paper is as follows: In the introduction section, the objective and outcome of the research carried out are discussed. In the literature review, the problem being faced by humankind during the pandemic time is described. In the methodology section, the architecture of the system developed along with the data flow is presented. In the result and discussion section, the details of the experiment carried out in the present research work and its performance are presented. In the conclusion section, the outcome and limitation along with the future work are included for better readability.

2. Literature review

In the Literature review, Problems being faced by humans during a pandemic period are listed: Testing: Performing swab tests to diagnose patients with Covid-19 has not been an easy job. It increases the risk of exposure to the deadly coronavirus. If

initial processes such as testing were done by robots, the healthcare professionals and nurses could focus on ancillary tasks (Pondaven-Letourmy et al., 2020). Decontamination of hospitals: With all the hospitals flooding with a surge of infected patients, it is indeed a huge task to disinfect and decontaminate hospitals very regularly. This requires a huge workforce and a lot of time. More importantly, these workers need to be in the vicinity of the infected patients to do the disinfection which again poses a threat of being infected (Gebel et al., 2013). Delivering food and medicines to patients: The delivery of food and medicines to Covid-19 infected patients in isolation wards has been very challenging for all hospitals around the world. The timely delivery of food and medicines is very important for infected patients. The collection of contagious wastes is also a threatening job for healthcare workers (Ceylan et al., 2003). Less workforce: With the rapid spread of the virus, numerous cases are being reported every single day. It is sad to realize that frontline workers are insufficient to treat an enormous group of infected people. There has been a shortage of PPEs and this reduces the efficiency of the treatment of infected patients (Huxley et al., 2020). The Covid-19 has been a strong catalyst for the development of robots. Right from doing small tasks to working along with healthcare professionals in the frontline, robots have proven their potential. For accurate COVID-19 testing: Performing Covid tests, collecting blood samples, and transporting infectious samples to labs are done by mobile robots. This undoubtedly relieves doctors from the pressure of being infected while performing tests. Automating such tests by using robots eliminates the delay in diagnosis (Feil-Seifer and Matarić, 2011). For monitoring infected patients: The concept of teleported (Ahmed et al., 2016) robots allows doctors to monitor and treat patients remotely. With a shortage of PPEs and nurses to monitor patients, robots can be used to seamlessly monitor patients and provide them with the services they require. They prove to be faster, safer, and more suitable for such tasks (Tavakoli et al., 2020). For disinfection routines: Robots are helping and will continue to help cope with the surge in infectious patients. Disinfection routines at hospitals and isolation wards are time-consuming and resource-intensive since they have to be done several times a day to maintain hygienic practices. Replacing health workers with robots for disinfection routines is a safer and healthier choice to make during this pandemic since robots are faster and those designed with superior technology are more efficient in killing germs than traditional approaches that are prone to errors (Livingston et al., 2020).

For intelligent interaction with people: It is indeed the most difficult time for patients to stay isolated from the outside world with almost no human interaction. Robots being designed with AI technology help in mitigating the lack of social stimulation for such people. A robot named Pepper is one such robot that is mounted with a tablet that enables people to video call friends and family. It accompanies patients and entertains them with dance moves too. In Belgium, one such robot is capable of speaking several languages. It also warns people if they are found without wearing a mask. In Arizona, telepresence bots entertain children who are confined to the rooms during the pandemic (Poulsen and Burmeister, 2019). Even as we consider replacing certain human tasks with robots, the decision-making process is still a major role that only humans have control over. We need to think about whether robots are capable of making emergency and sensitive decisions without human intervention (Wallach, 2008). Data protection and privacy is another major concern while considering the development of robots (De Santis et al., 2008). To what extent can a robot be socially present and how much can it emote and understand human feelings needs to be considered while adopting robotic developments (Cañamero, 2005). If robots replace humans and take over human tasks, who will eventually hold the ultimate responsibility and access to the data collected by the robot is another question that needs to be addressed (Doran and Gokhale, 2011). Abbas et al. (2021) had proposed a model named DeTraC deep convolutional neural network. The outcome of the proposed model is to classify the Covid-19 patient using images of chest X-rays. About five different pre-trained models (AlexNet, VGG19, ResNet, GoogleNet, SqueezeNet) are used with two tuning models (Deep and shallow) and the performance is measured using evaluation parameters like accuracy, sensitivity, and specificity. The observation made in the result section is using the proposed model (DeTraC) in Deep tuning mode the accuracy is boosted with value (+25.36%). The combination of Fuzzy Inference Engine (FIE) and Deep Neural Network (DNN) is applied to develop a hybrid classification model (HDS) in detecting COVID-19 patients (Shaban et al., 2021). In the proposed model the features like C-Reactive Protein, Lactate Dehydrogenase, Eosinophil, Leukocytes, Neutrophils, Basophils, Lymphocyte, Platelets, Monocytes, Alanine Aminotransferase. The evaluation parameters Accuracy (97.65%), Precision (96.75%), Recall (96.5%), and Error (2.34%) are used to measure the performance of the developed model. In addition to that Friedman's mean ranking is used in estimating the performance of different techniques like Dark Covid Net (6.0), CNN (4.8), and the proposed model HDS (1.2).

A hybrid model named Generative Adversarial Networks (GAN) combination of Deep Transfer Learning networks (Inception v4, InceptionResNet v2, MobileNet v2, VGG16) and LSTM is proposed in detecting COVID-19 patients. In which, GAN is used to generate artificial images. The generated images are grouped into seven different scenarios to test, train and validate the proposed model. In addition to that White Gaussian noise is added to chest X-ray images in the different ranges (-4 to +20 dB) of Signal to Noise Ratio (SNR) and achieved 99.5% accuracy (Sheykhivand et al., 2021). Computed

Tomography (CT) scans and chest X-rays (CXRs) are used collectively to train and test the hybrid model, CNN tailored (Convolution and Max Pooling) along with DNN and achieve accuracy over 96.28% (Mukherjee et al., 2021). Bai et al. (2020) had developed an Artificial Intelligent system in separating COVID-19 patients from other pneumonia. The performance of radiologist performance without and with AI assistance is compared and achieved test accuracy of 96% with 95% confidence Interval. To summarize the performance of the radiologist has improved with the assistance provided using an Artificial Intelligent system. Xie et al. (2021) has developed a Deep Learning model in classifying COVID-19 victims. In which, 563 CT scan images are used to train the model. The lung region is extracted using U-net and the output from U-net is given as input to trained ResNet-50-based IDANNet to generate the dialogistic probability value of each test instance. The proposed model has achieved the accuracy of 95% with 0.85 to 0.87 Confidence Interval. The advantage of the proposed model is the model is trained without annotation made by human radiologists for diagnosis. The main challenge in classification is imbalance dataset. The common technique which can deal with such datasets is developed by (Rahimzadeh and Attar, 2020). In which, deep CNN model is combined with ReNet50V2. The model is working based concatenation of Xception. The performance of Xception (91.31), ResNet50V2 (89.79) and combination (91.40) is estimated using average classification accuracy.

3. Methodology

The robotic agent side of the proposed system consists of a single 3D printed humanoid machine. Microcomputer handles that hold system caches, actuator registrations, and TTL-based communications between them. Electric power is divided into two parts that feed the computer and the motors. In addition, the IoT side of the system will include the Amazon Echo Dot platform due to its low cost and the positive benefits of Amazon Web Services (AWS) and its features. In addition, the easy connection to Alexa's objectives and being a friendly Python framework, taking into account future Robot Operating System (ROS) issues, protects this option. The optional building of information mapping and CNN recommendation unit is summarized by a formulated classifier and decision-making unit. The main role of information processing in CNN is to generate independent datasets or elements for unambiguous decision-making. The proposed system in Fig. 2 is thereby summarized in a detail in Fig. 3, the CNN model of recommendation framework. This framework is processed with a feature extraction process. The independent and collateral features of input samples are extracted and processed within a parallel observation paradigm of trained samples. The dependent thresholding matrix of trained datasets and input

paradigms are combined to generate two categories of data features, the primary features are generic features with behavioral parameters (B_T) and sematic features with relational parameters (R_T). This process assures the processing of information into a CNN hidden-layer module for normalizing the parameters with reference to threshold values and result in a generation of classifiers. Finally, the information based on the classifier is processed with a decision-making unit in proving a reliable recommendation of COVID 19 based on medical datasets.

4. Mathematical model

Consider the input of Multi-dimensional Medical (MdM) datasets $M = \{M_1, M_2, M_3 \ldots M_n\}$ such that each of M_i is an element variable of dual medical datasets such as CT and X-Ray with reference to thermal images. These datasets are a combination of CT and X-Ray respectively represented as U, such that, ($M \subseteq U \forall U \in MdM$) where MdM is a multi-dimensional medical dataset. The input is coordinated and collected via a robotic agent *(A)* such that, each event is assigned and trained by an individual robot agent or mobile processing agents assigned and trained by an individual robot. The robots are monitored and supported by Robot Operating System (ROS) with support coordinated from Alexa's AWS. Consider the processing with reference to the CNN model as shown in Fig. 3. The primary layer of extraction is feature extractions *(f)* such that, each layer of independent user's features is extracted and correlated. The feature extraction set can be summarized in Eq. 1 and Eq. 2 respectively.

$$f = \sum_{i=o}^{\infty} \partial(M_i x_i + \Delta T) \prod \Delta f_x \tag{1}$$

$$\therefore f = \lim_{n \to \infty} \{ [\sum_i^{\infty} \frac{\partial(M_i x_i)}{\partial U}] + [\sum_j^{n-i} \frac{\partial(\Delta T_j)}{\partial U}] \prod \Delta f_x \} \tag{2}$$

where, *($M_i x_i$)* is the feature collateral vector of robot input sample set from M with x user interpretations such that, each event of feature set (ΔT) as represented in Fig. 3 and Δf_x is the feature recurrence count, to assure the range between 0 and 1, and if greater, the 1 is re-calibrated in Eq. 2 with reference to Universal set *(U)* with independent computation of feature set. Thus, on successful extraction, the thresholding values from trained data samples are (ΔT) then computed and optimized (Xie et al., 2021).

Hence, the feature set optimization is reported and monitored with a series of processing such as thresholding and value summarization with reference to generic features and semantics feature classification. The mapping is trained and datasets are shown in Eq. 3. The major purpose of threshold mapping is to assure the recommendations of covid and con-covid are classified based on a generic feature set such as behavioral parameters (B_T) and sematic features such as relational parameters (R_T).

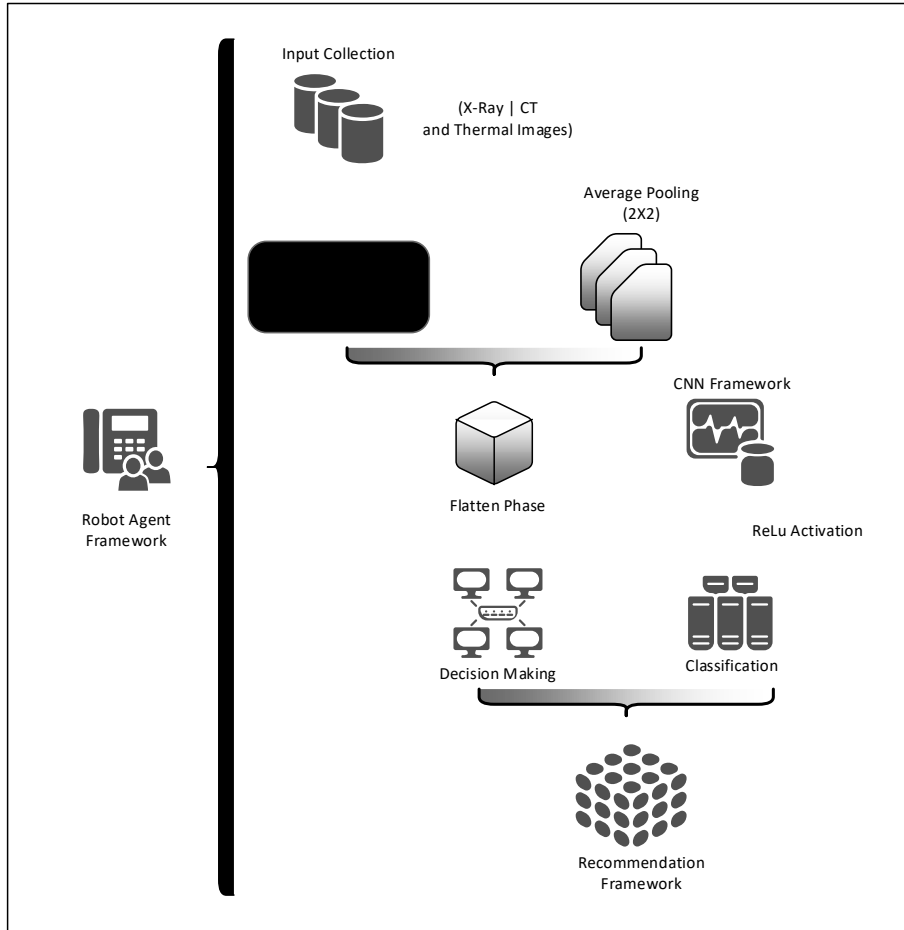Thus, each attribute is independently evaluated as shown in Eq. 3.

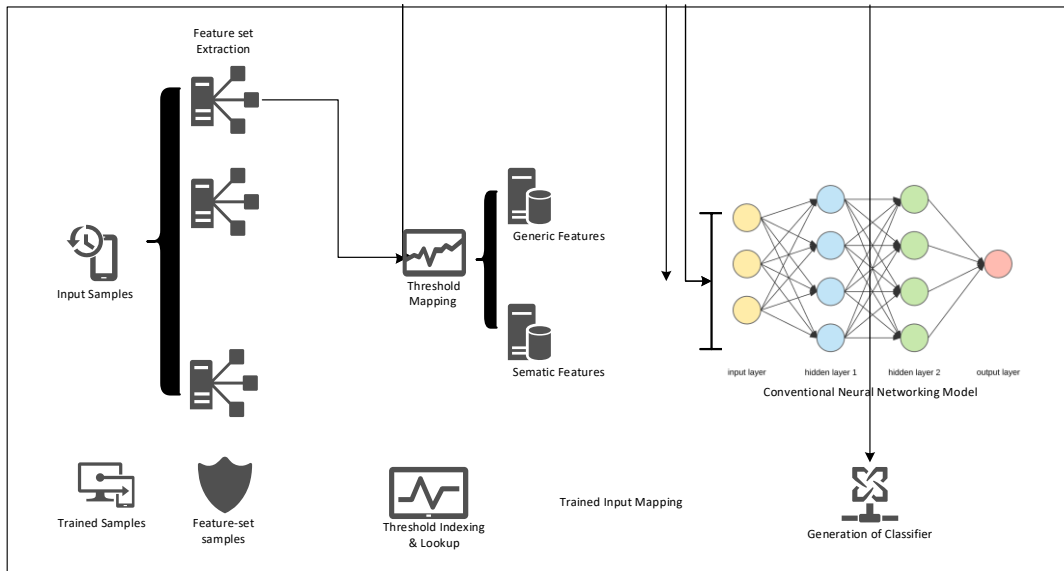**Fig. 2:** Data flow of the proposed system

Fig. 3: CNN model of recommendation framework for COVID-19

$$f_x = \frac{\lim_{n \to \infty}\{\sum_{i=0}^{\infty}\sum_{j=i+1}^{n}(\frac{\partial(B_T)_i}{\partial(M_j)}) + (\frac{\partial(x)_j}{\partial(M_i)})\}}{\lim_{n \to \infty}\{\sum_{i=0}^{\infty}\sum_{j=i+1}^{n}(\frac{\partial(R_T)_i}{\partial(M_j)}) + (\frac{\partial(x)_j}{\partial(M_i)})\}} \quad (3)$$

$$\therefore \Delta f_x = \frac{\lim_{n \to \infty}\{\sum_{i=0}^{\infty}\sum_{j=i+1}^{n}(\frac{\partial(B_T)_i + \partial(x)_j}{\partial(M_j)})\}}{\lim_{n \to \infty}\{\sum_{i=0}^{\infty}\sum_{j=i+1}^{n}(\frac{\partial(R_T)_i + \partial(x)_j}{\partial(M_i)})\}} \quad (4)$$

In Eq. 3 and Eq. 4, the representation semantic relational parameters (R_T) and generic behavioral parameter (B_T) based extraction and feature set generation with reference to M_i vector. The computational is then coordinated by a thresholding vector ΔT, trained under the coordination matrix towards optimization of a neural networking model as shown in Eq. 5.

$$N = \Delta T \prod \log_2(x_i) \begin{matrix} \partial(f_x)_{BT} \to \frac{\partial(f_x)_i}{\partial(B_T)_i} \\ \partial(f_x)_{RT} \to \frac{\partial(f_x)_i}{\partial(R_T)_i} \end{matrix} \qquad (5)$$

Typically, the formulated vector of computation is replicated into a hidden layer of neural networking computation such as the data-stream represented in Table 1. The matrix of evaluation is retrieved via computational classification values, subjected to decision-making based on evaluation parameters. The recommendation framework's efficiency is shown in Fig. 5 and is subjected to formulate a semantic classification approach of covid-19 patients based on MdM datasets as x-rays and CT images.

A Convolutional Neural Network (CNN) is trained using images collected using a camera and thermal camera with RGB values ranging from 0 to 255. A framework that automatically detects people who are not considering precautionary measurement for the spread of COVID-19. The classification is performed on the CT scan images and X-rays as shown in Fig. 4. The evaluation parameters used to estimate the performance of the proposed model are Accuracy, Precision, Recall, F-Score as listed in Table 1.

5. Results and discussion

The performance of MLA (Decision Tree and Random Forest) for both training and testing data is estimated. By using Decision Tree (DT) and feature selection as entropy leads to the classification accuracy of 88%. The attempt towards improving the Classification Accuracy (CA) is made using pruning with the cost estimation approach. In which, the alpha value (CCP_Alpha) is taken into consideration and estimated the performance of the DT algorithm as shown in Fig. 4.

The X-axis represents the different possible values of alpha values and the Y-axis as CA. The training and testing data performance is represented with blue and orange colors. It is noticed that with alpha value zero the training set performance is 100% and the testing set performance is 0%. The improvement in alpha value is exactly at 0.013. The performance of testing data improves and reaches 94%. The advantage of using DT is posting pruning is by eliminating the features that lead to overfitting the DT model constructed. Similarly, the Random Forest (RF) classifier has trained to provide better accuracy and obtained a CA of 85%. The main drawback of RF is that it does not support pruning. The performance of the CNN models used to train the developed mobile robot is presented in Fig. 5.
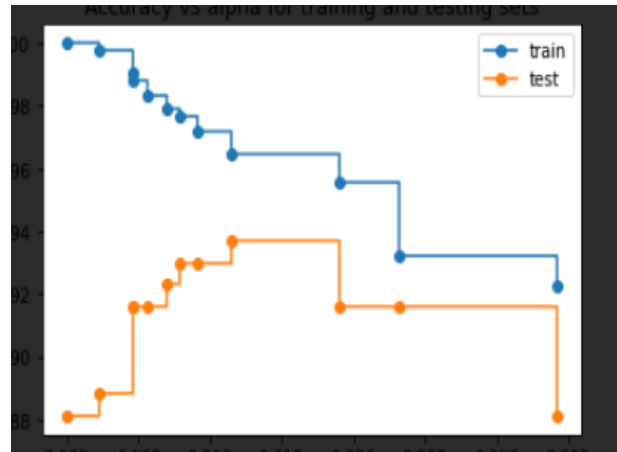

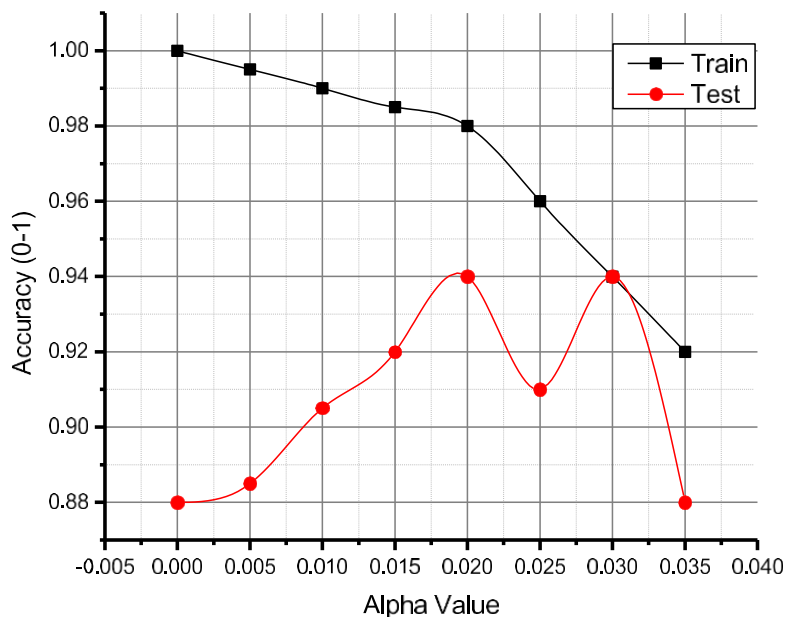**Fig. 4:** Performance of post pruning approach of decision tree

Fig. 5: Accuracy of CNN models

Table 1: Evaluation parameters

Parameters	Formula
Accuracy(A)	$A = \dfrac{TP + TN}{Total}$
Recall(R)	$R = \dfrac{TP}{Actual\,True}$
Precision(P)	$P = \dfrac{TP}{Predicted\,True}$
F Score(FS)	$FS = 2 \times \dfrac{R \times P}{R + P}$

In which, the proposed model has achieved an accuracy of 84% during testing the model with new instances. The reason behind the improvement of accuracy in the proposed method is because of the filter used to extract the features used in the architecture as mentioned in Fig. 1. Similarly, the precision, recall, and F-score were also plotted and the proposed model has achieved a 0.82 F-Score as shown in Fig. 6.
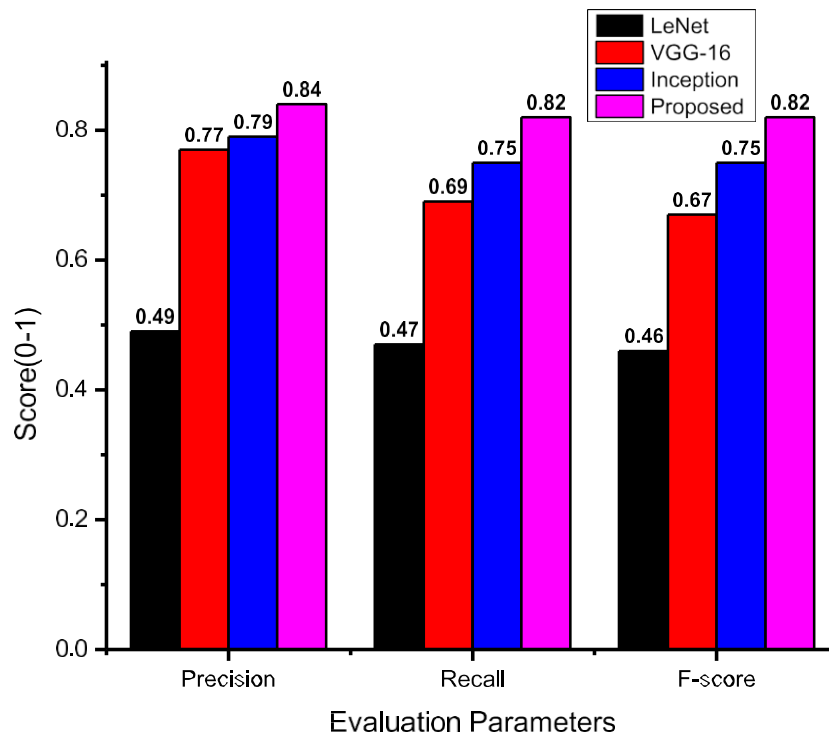
Fig. 6: Precision, recall, and F score of the CNN models

6. Conclusion

The Covid-19 pandemic has brought to light that the usefulness of robots has outweighed its downsides in various fields. Machine vision systems and deep learning techniques incorporated in the design and development of mobile robots offer speed, accuracy, and efficiency thus making robots crucial tools for several tasks during pandemics and other such situations. However, it is vital to focus on the design and development of robots and make them less threatening for people to use. While using mobile robots in caregiving scenarios, they need to be designed such that they mitigate the patients' psychological stress. The proposed model achieves 0.84 Precision over the inception technique with 0.79 precision.

Acknowledgment

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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