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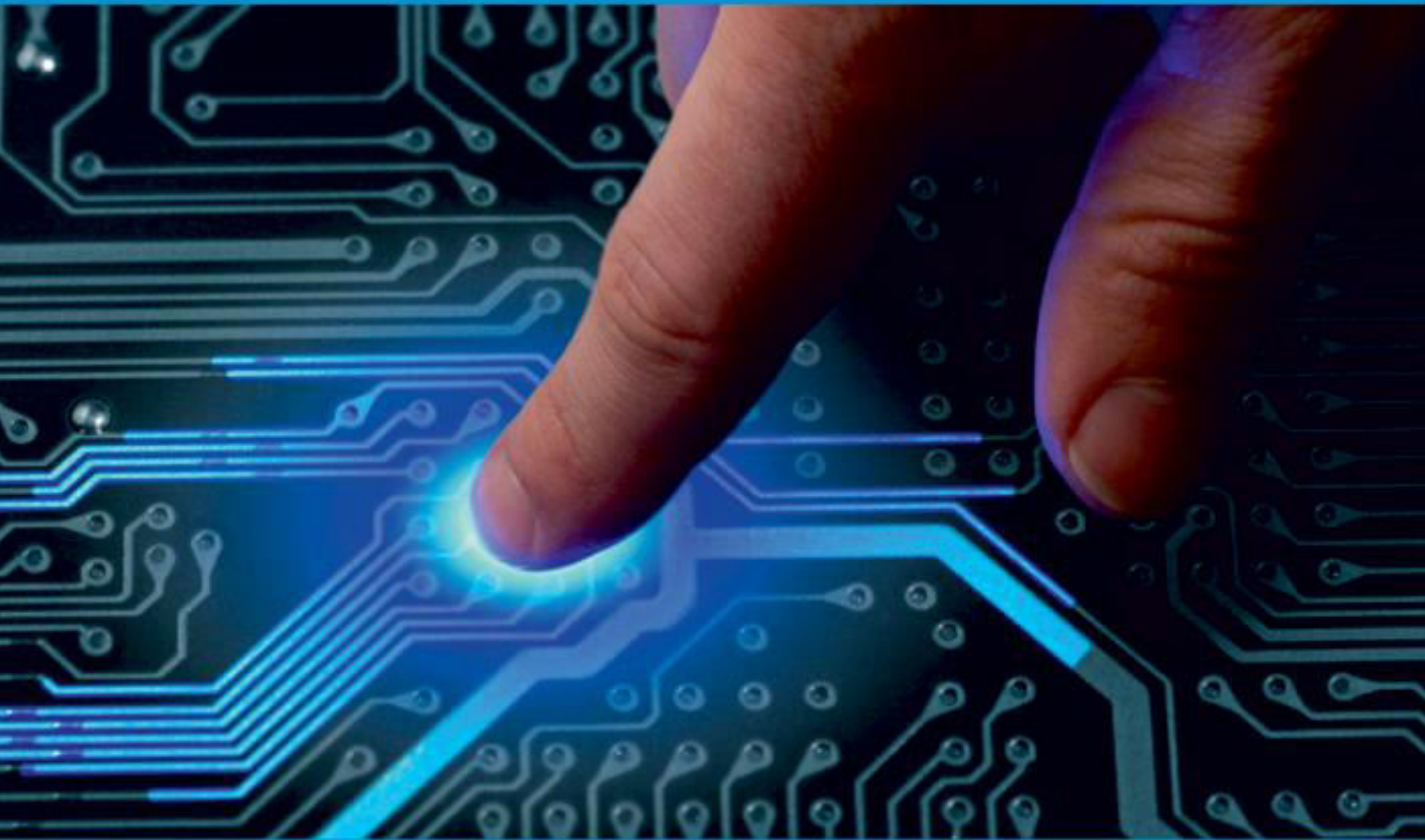

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COVID-19 Future Forecasting Using Machine Learning

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ABSTRACT: Machine learning (ML) based prediction mechanisms have proved their significance to anticipate in perioperative outcomes to enhance the decision making on the future course of actions. The ML models have long been used in many application domains which needed the identification and prioritization of adverse factors for a threat. Various prediction methods are being popularly used to handle prediction problems. This study demonstrates the capability of ML models to forecast the number of upcoming patients affected by COVID-19 which is presently considered as a potential threat to human beings. To be specific, four standard forecasting models, such as linear regression (LR), least absolute shrinkage and selection operator (LASSO), support vector machine (SVM), and exponential smoothing (ES) have been used in this study to forecast the threatening factors of COVID-19. Three types of predictions are made by each of the models, such as the number of newly infected people, the number of deaths, and the number of people to be recovered in the next 10 days.

KEYWORDS: Deep learning, Artificial Neural Networks, Long-Short-Term Memory (LSTMs), Pandemic, COVID-19, Coronavirus

I.INTRODUCTION

This problem of forecasting has been considered as a regression problem in this study, so the study is based on some state-of-art supervised Machine Learning regression models such as linear regression (LR), least absolute shrinkage and selection operator (LASSO), support vector machine (SVM), and exponential smoothing (ES). The learning models have been trained by using the COVID-19 patient stats dataset provided by Johns Hopkins. The dataset has been pre-processed and divided in to two subsets: training set (85% records) and testing set (15% records). We are trying to develop a prediction system for COVID-19. The prediction is done for the three important variables of the disease for the coming 10 days the number 0f new confirmed cases, the number of death cases, the number of recovered cases.

II. MOTIVATION

In our existing system there no prediction available so government faces many issue related to provide facility to public.

A. Objectives

The forecasting is done for the three important variables of the disease for the coming 10 days:

1. The number of New confirmed cases
2. The number of deaths
3. The number of recovered humans

III. CONCEPTS

A. Artificial Neural Networks (ANN)

ANNs are programmed to try and simulate a human brainby modelling the neural structure on a smaller scale. ANN consists of interconnected web of nodes joined by edges known as neurons. The main function ANN is to perform progressively complex calculations on a set of inputs, then use the output to solve a problem. ANNs are used for lots of different applications. An ANN typically consists of 3 layers namely input, hidden and output layers. Neural net can be

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seen as a result of spinning classifiers composed in a layered web; this is because every node in the hidden layer and output layer has their own classifier.

B. Recurrent Neural Networks (RNN)

Recurrent neural networks (RNN) find their best usagewhen the patterns in data vary with time. This deep learningmodel is a simple structured model with a built-in feedbackloop that allows it to act as a forecasting-engine. In thefeed forward neural network signals have unidirectionalmovement from input to output one layer at a time, In RNN the layer's output is added to the next input and fed back into the same layer, Contrary to feed-forward neural nets, an RNN can accept a sequence of values as input and produces a sequence of values as output, the capability to operate in sequence unfolds RNN to a wide variety of applications. It is possible to obtain a capable net of more complex outputs by stacking RNNs one on top of another.

C. Long Short-Term Memory Networks (LSTMs)

Long Short-Term Memory Networks (LSTMs)characteristically, an RNN is a very challenging neural net to train. Since RNNs make use of back propagation,they run into the problem of vanishing-gradient. Unfortunately, the vanishing-gradient is exponentially worse for an RNN. The reason being that, each time step is the equivalent to an entire layer in a feed-forward neural network. So, training an RNN for a 100-time step is similar to training a 100 layer feedforward neural net. This results in exponentially small gradients and information decay through time. These problems can be solved using Long-Short-Term-Memory networks (LSTMs). LSTM are modules of RNN that can learn the long-term dependencies. By placing the LSTM modules inside an RNN, long-term dependency challenges can be avoided.

D. Time series data (TS)

Time series data refers to the data that is collected over aregular time period and captures a series of data pointscaptured at regular intervals of time where every data point isequally spaced over time. Trend, seasonality and error arethe important components of a time-series data. Forecastingupcoming patterns and trends based on historical datasetcontaining temporal features is known as Time Seriesprediction. Data with temporal components will be the best suited data to forecast the novel coronavirus transmission. A time-series data pattern can be noticed when a certain trend recurrence at regular time periods like confirmed cases, deaths, recovered cases etc. In many real-time situations, either seasonality or trend is absent. After finding the nature of time series data, different forecasting methods must be applied. The two categories of time-series data are non-stationary data and stationary data. A stationary series is independent of the time components such as seasonality, trends etc. Constant mean and variances are observed with respect to time. A non-stationarydepends on the seasonality effects and trends in it and varieswith respect to time. Statistical properties like mean, variance and standard deviation also changes with respect to time. Compared to non-stationary TS, stationary TS data is easier to analyse and provides good forecasting results.

IV. REVIEW OF LITERATURE

Author proposes Head pose classification is widely used for the pre-processing before face recognition and the multi-angle problems, because algorithms such as face recognition often require the input image to be a front face. But infected by the COVID-19 pandemic, people wear face masks to protect themselves safe, which makes cover most areas of the face. It makes some common algorithms cannot be applied to head pose classification in the new situation. Therefore, this paper has set up a method HGL to deal with the head pose classification by adopting colour texture analysis of images and line portrait. The suggested HGL method combines the channel of the HSV colour space with the face portrait and grayscale image, and train the CNN to extract features for further classification. The evaluation on MAFA dataset confirms that compared with the algorithms based on facial landmark detection and convolutional neural network, the suggested method has achieved a better performance (Front accuracy: 93.640%, Side accuracy: 87.170%).

Author Proposed Medical IoT devices are rapidly becoming part of management ecosystems for pandemics such as COVID-19. Existing research confirms that deep learning (DL) algorithms have been successfully used by researchers to identify COVID-19 phenomena from raw data obtained from medical IoT devices. Some examples of Internet of Things technology are radiological media similar to CT scan and X-ray images, body temperature measurement through thermal cameras, safe social distancing identification using live face detection, and face mask detection from camera images. However, the researchers have recognized several security vulnerabilities in DL algorithms to adversarial perturbations. In this paper, we have done the testing of a number of COVID-19 diagnostic methods that rely on DL algorithms with relevant adversarial examples. Our test results show that Deep Learning models that do not consider defensive models against adversarial perturbations remain vulnerable to adversarial attacks. In the long run, we present in detail the adversarial example generation process, execution of the attack model, and the agitations of existing DL-based COVID-19 diagnostic applications. We anticipate that this work will raise awareness of adversarial attacks and encourages others to safeguard DL models from attacks on healthcare systems.

In paper author, Corona virus Disease 2019 (COVID-19) caused by severe acute respiratory syndrome coronaviruses 2 (SARSCoV-2) has happened a significant global pandemic in the past couple of years and caused tremendous loss to humans globally. For such a large-scale pandemic, early detection and isolation of the potential virus carriers is important to curb the spread of the virus. Recent studies have exhibited that one important feature of COVID-19 is the abnormal respiratory status caused by viral infections. During the pandemic, many persons wear the masks to reduce the risk of getting sick. Therefore, in this paper, we suggest a portable non-contact method to screen the health conditions of the humans wearing masks through analysis of the respiratory characteristics from RGB-infrared sensors. Initially, we accomplish a respiratory data capture technique for people using the masks by using face recognition. Then, a bi-directional GRU neural network with an attention mechanism is applied to the respiratory data to obtain the health screening result. The outcomes of validation experiments depict that our model can identify the health status of respiratory with 83.69% accuracy, 90.23% sensitivity and 76.31% specificity on the real-world dataset. This work demonstrates that the suggested RGB-infrared sensors on portable device can be used as a pre-scan method for respiratory infections, it provides a theoretical basis to encourage controlled clinical trials and thus helps fight the current COVID-19 pandemic. The demo videos of the proposed system are available at: https://doi.org/10.6084/m9.figshare.12028032.

This paper [4] Tactile edge technology that focuses on 5G or beyond 5G reveals an exciting approach to control infectious diseases such as COVID-19 internationally. The control of the epidemics such as COVID-19 can be managed effectively by exploiting edge computation through the 5G wireless connectivity network. The implementation of a hierarchical edge computing system provides various advantages, such as low latency, scalability, and the safeguarding of application and training model data, which enables COVID-19 to be evaluated through a local edge servers. In addition, various deep learning (DL) algorithms suffer from 2 important disadvantages: 1st, training requires a large COVID-19 dataset consisting of many aspects, which will pose challenges for local councils; second, to acknowledge the outcome, the findings of DL require ethical acceptance and clarification by the health care sector, as well as other contributors. In this paper, we suggest a B5G framework that utilizes the 5G network's low-latency, high-bandwidth functionality to detect COVID-19 using chest X-ray or CT scan images, and to develop a mass surveillance system to monitor social distancing, mask wearing, and body temperature. Three Deep Learning models, ResNet50, Deep tree, and Inception v3, are investigated in the proposed framework. Moreover, blockchain technology is used to ensure the safety of healthcare data.

Author present from the beginning of the current COVID19 pandemic, more than five million people have been infected and the numbers are still on the rise. Early symptoms detection and hygienic standards are thus of utmost importance, especially in places where people are in random or opportunistic contact with each other. Finally, automated systems with medical-grade body temperature measurement, hygienic compliance evaluation and individualized, person-to-person tracking, are vital, for disease spread intervention and prevention, in addition to this to assure economic stability. Herein, we present a system that encapsulates all of the mentioned functionality via readilyavailable components (both hardware and software) and is further enhanced with preliminary RTLS data acquisition, enabling post-symptom detected, person-to-person interaction identification to assess potential infection vectors and mitigate further propagation thereof by means of smart quarantine.

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V. PROPOSED METHODOLOGY

Algorithm used in proposed system are as follows:

- SVM Algorithm
- Linear Regression • Classification Techniques

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A. Architecture

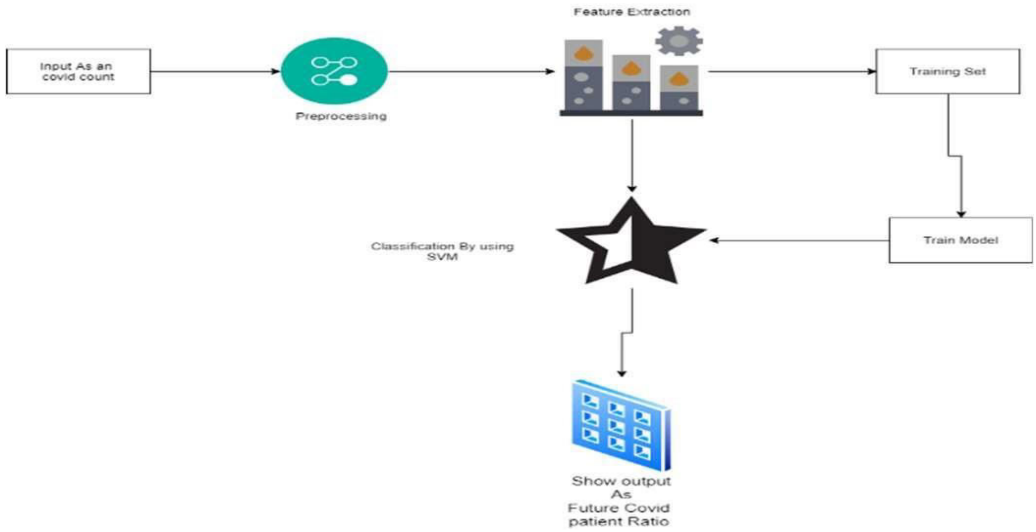

Fig. 1. System Architecture

VI. RESULT AND ANALYSIS

6.1 EVALUATIONPARAMETERS

Root mean square error or root mean square deviation is one of the most commonly used measures for evaluating the quality of predictions. It shows how far predictions fall from measured true values using Euclidean distance.

US - RMSE: 158.59103071746736

Brazil - RMSE: 477.4231696149296

Russia - RMSE: 235.0312199582234

United Kingdom - RMSE: 1638.3705327552755

Spain - RMSE: 90.97710492698131

Italy - RMSE: 19.82084646847693

France - RMSE: 1721.4720081834366

Germany - RMSE: 43.65146231797281

Canada - RMSE: 38.00525458836768

China - RMSE: 235.3339666487335

Turkey - RMSE: 10.65307991515472

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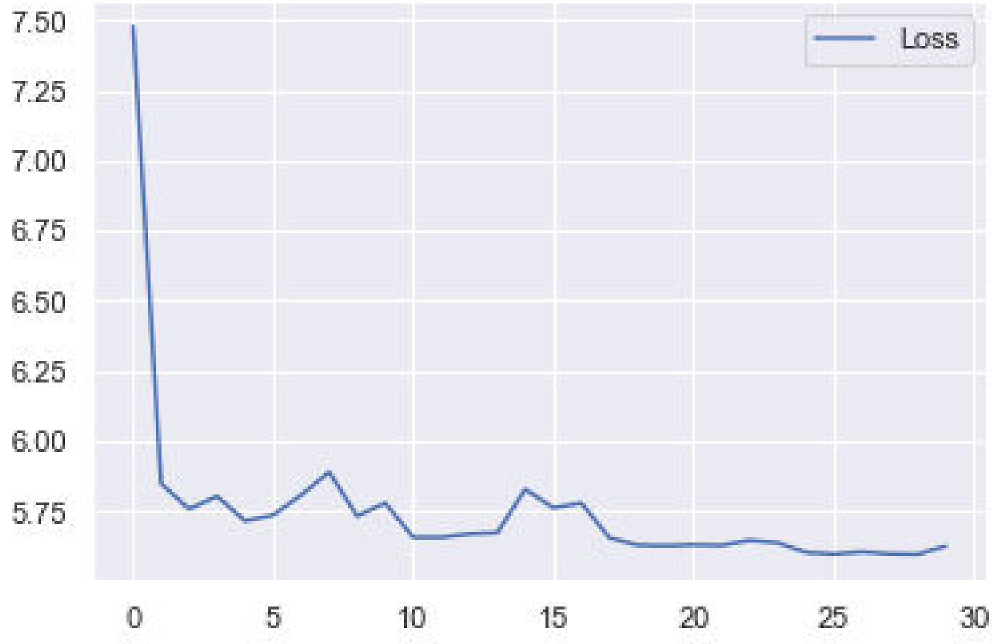

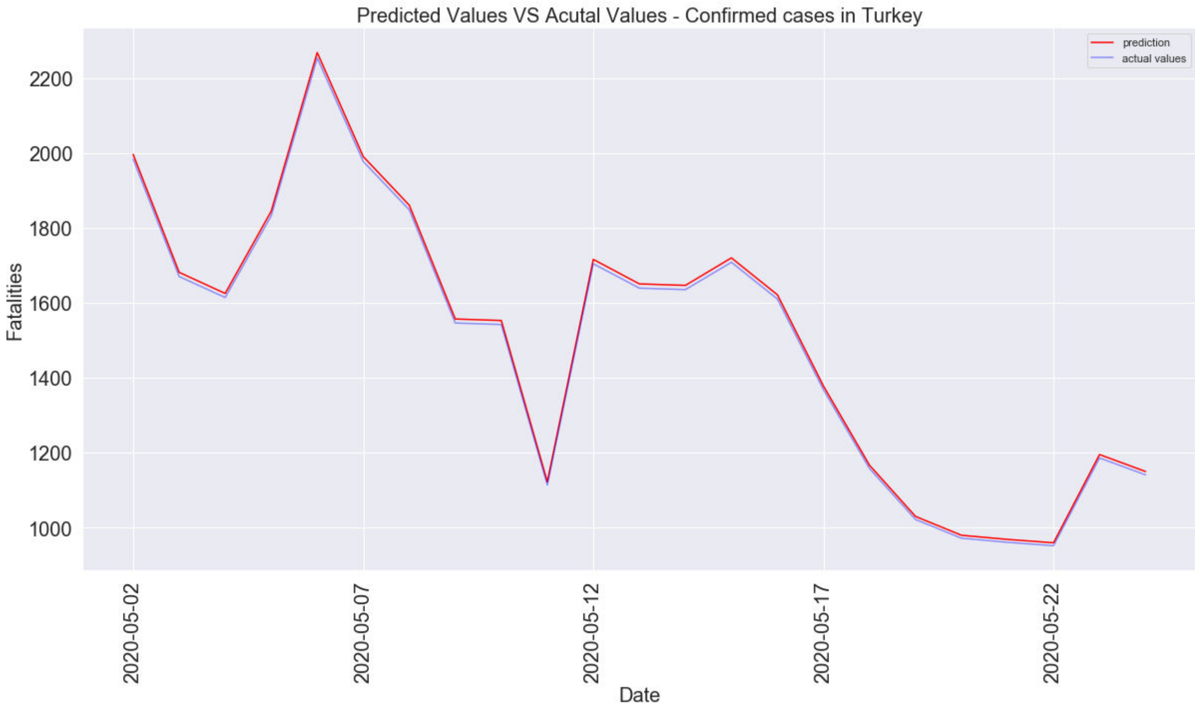

VII. CONCLUSION

Predicting COVID-19 cases has immense significance in the present dire scenario. In this work the growth patterns of the disease have been analyzed, data-driven estimations have been incorporated. Deep learning model based on RNN, LSTMs and time series analysis have been used to predict the trends in coming days such as the no. of confirmed positive cases, number of deaths caused by the virus and number of people recovered from the novel corona virus. Encouraging experimental results have been obtained on the dataset used.

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VIII. FUTURE SCOPE

The problem of predicting Covid-19 related data such asfuture cases, recovered cases and deaths is difficult, since we are amidst an outbreak. The future trends and patternsmay vary widely based on myriad external conditions like quarantine measures, new behaviour of the virusstrain, population of a country etc., as the datasetbecomes larger and we have more data to train our model, wecan improve the accuracy. The same model can be used topredict any future pandemics that are similar in nature to

SARS COVID-19. This model can be integrated with anapplication that streams live data from government sites toview real time graphs of COVID-19 related data. Hope thateverything will recover and get back to normal soon.

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