A Robust Statistical CNN CTC Based AI Model for Tracking and Monitoring Covid-19

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A ROBUST STATISTICAL CNNCTC BASED AI MODEL FOR TRACKING AND MONITORING COVID-19

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Abstract— *The world today battles the new coronavirus (COVID-19) spread that can lead to a major endemic or pandemic outbreak with devastating outcomes which has overturned all our usual calculus seemingly. Due to the unavailability of a vaccine and the high degree of contagiousness, social distancing is perhaps the only way left to battle the virus. The tracking system is still a challenge for monitoring the COVID-19 affected person and the community spread. This leads to an epidemic situation, where the number of secondary infections keep going higher and higher which intern leads to the difficulty of tracking and treating each infected person. An AI based mathematical modelling is proposed for tracking and monitoring the pandemic outbreak. A GPS tracking system, geo location using Fit bit and wifi tracking modules are developed to locate the secondary infections and the carriers. Calculation of real time co-ordinates and the conditional probabilities with respect to time is done followed by the classification based on risk using CNN CTC (Connectionist Temporal Classification) model, a type of neural network which is used to train the recurrent process. Monitoring the affected person using sensors like thermal sensors and a tracking chip inbuilt in a wristband for real time updates. A comparative study is done on various Classification models. Therefore, the system provides a robust model with 96.5% accuracy to combat this pandemic situation.*

***Index Terms* – COVID-19, GPS, Fit bit, CNN, Connectionist Temporal Classification (CTC), thermal sensors.**

I INTRODUCTION

The pandemic of corona virus malady 2019 (COVID-19) is spreading everywhere throughout the world, facing the day to day challenge and threat posed by the virus which originated in Wuhan. The Centres for Disease Control and Prevention (CDC) have said that SARS-CoV-2 is a respiratory infection, and it is mainly transmitted between people through "respiratory beads" when indicative individuals sniffle or hack. In case of a pandemic outbreak, emergency management units must arrange a viable alleviation technique to stop the ailment spread utilizing constrained assets. In order to develop a fruitful response, it is necessary to design an accurate mathematical model of how the disease will spread. Previously developed models mostly rely on homogeneous blending models, which treat every member of the population as having indistinguishable disease chance. Intuitively, such an assumption is unrealistic. Certain demographic gatherings (e.g., healthcare workers, children and the elderly), have higher rate of infection risks. Additionally, behavioral patterns such as use of public transportation impact infection risks. Using contact networks to represent the level of contact between population members and census data to estimated geographic location and travel patterns, we stimulate the movement of a bead spread malady through the Greater Toronto Area. The outcomes are intermittently shown on zone maps utilizing GIS for visualization and planning purposes. The proposed system provides an AI based tracking and monitoring system in order to avoid the social community spread. A statistical model is developed based on the classification on the levels of risk into three zones. CNNCTC based classification model is proposed to classify and train the recurrent process of identification based on variety of parameters. Monitoring the health of the individual is done using thermal sensors which tracks the body temperature and tracking chip located in the wristband to indicate the proximity. The system developed provides a robust and effective framework for tracking the contacts made by the COVID influenced individual. The classification based on time stamp is done using a mathematical model. Finally, a monitoring system for the isolated individual using sensors is done.

II. RELATED WORK

Simulation studies play a significant role in supporting pandemic disease scenario prediction and facilitating the understanding of how infectious diseases spread. Disease-spread simulation models are often used to understand the effects of changes in citizen behavior or government policies, or to study disease outbreak parameters and mitigation-strategy features. This outbreak demonstrated that increased population density and mobility can play important roles in the spread of emerging infectious diseases and could potentially lead to future pandemics. However, tracking every individual's detailed critical behavioral patterns for an entire population can be challenging and requires extensive computation power [7].

By understanding the spatiotemporal features of contacts between infectious and susceptible persons in mass transportation activities, we can quantify the intensity and probability of infection in certain urban settings. Currently, there are some agent-based microscopic models that aim to emulate the movement of passenger flow in frequent public travel activities.[3] – [6]

Deterministic models and stochastic Models [8],[9],[10]-[12] are commonly used to describe the transmission dynamics of infectious diseases.

The contact tracing app has been developed by the National Informatics Centre under the Ministry of Electronics and Information Technology (MeitY), and is available in 11 languages. Aarogya Setu uses a smartphone's Bluetooth and GPS systems to alert users when they come within six feet of COVID-19 patients. The alerts are generated by scanning through government-owned, location-specific databases. They are accompanied by instructions from the Ministry of Health on how to self-isolate, and the course of action required when citizens develop symptoms of coronavirus [13].

Quarantine Monitor, built by the Tamil Nadu e-Governance Agency, monitors people who are quarantined as per the state's official database. It assists the Department of Health and the Tamil Nadu Police for effective tracking and information management of COVID-19 cases and people with foreign travel history over the last two months. The app enables live location tracking once installed, and generates alerts and information, which are sent to state government authorities [13].

Providing timely and appropriate medical help during a disaster or during an emergency situation is a key challenge in healthcare scenario [2].

The development of mobile application in wireless network improves the medical system to operate throughout the world. E-healthcare system of Remote Patient Monitoring [1] where the system is to mitigate the problem occurring in remote area.

III. METHODOLOGY

The proposed system uses GPS tracking system to locate the secondary infections and the carrier followed by the classification based on risk into three zones. The stability of a dataset is maintained using coefficient of variation (CV), a statistical tool. Monitoring is done using sensors in wrist band for the complete health status.

The system provides the complete solution through these two modules.

(i) Tracking the nearest node who travelled along with the carrier node

1. Using the GPS location of the user, geo location using Fit bit and wifi tracking modules the location of the carrier node and the nearest node along with the carrier node can be identified through network access.
2. Once the nearest node is identified then this group of nodes are classified in three categories based on the timestamp using the Connectionist Temporal Classification [CTC],
    - First it classifies, timestamp of the nearest node always stays along with carrier node
    - Second it classifies, timestamp of the nearest node stays greater than 3 hours and lesser than 10 hours
    - Finally, timestamp of the nearest node stays in lesser time.

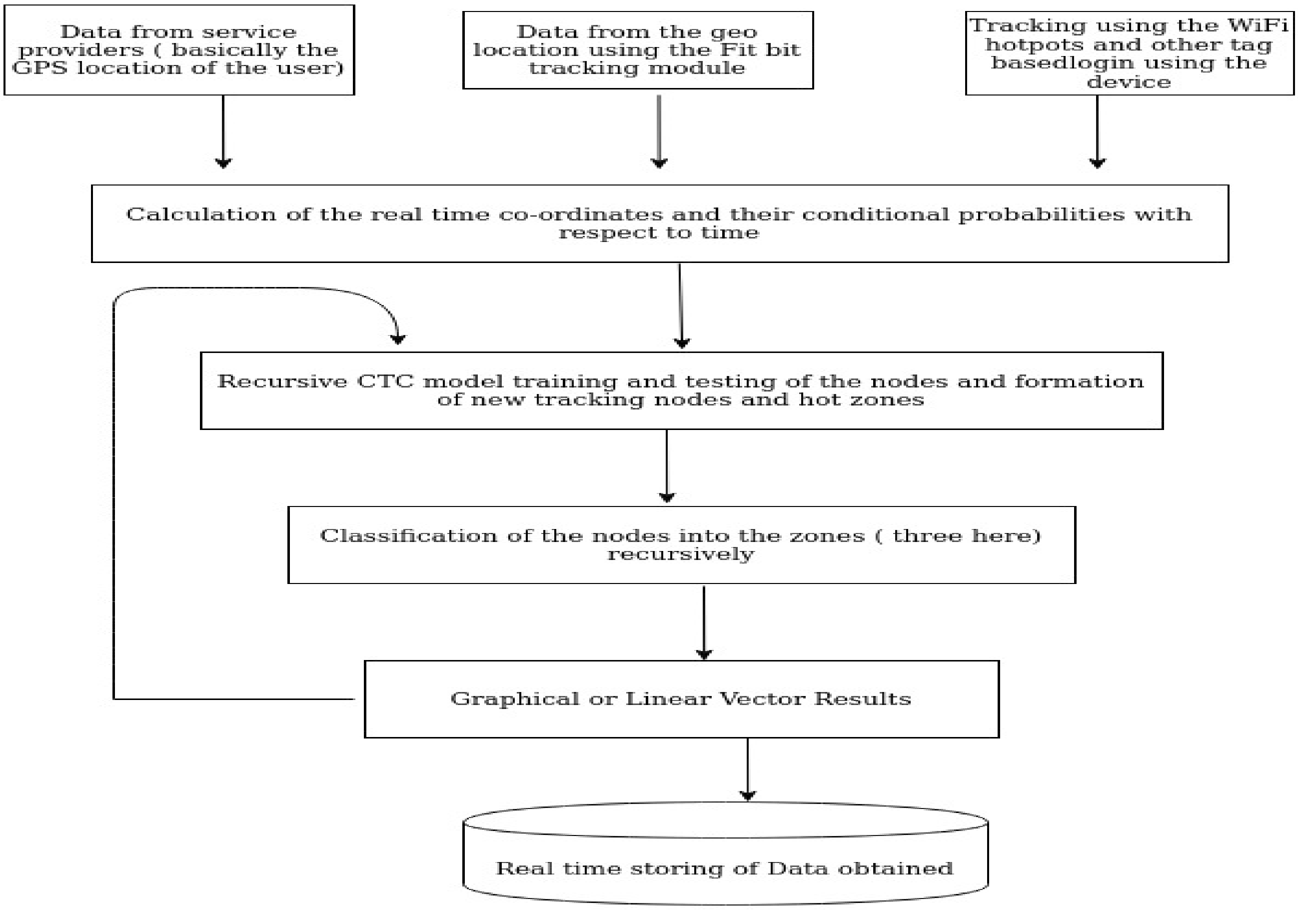

Fig1: CNNCTC based AI model for tracking and monitoring COVID-19

(ii) Tracking the nearest node who travelled along with the carrier node

3. Using the GPS location of the user, geo location using Fit bit and wifi tracking modules the location of the carrier node and the nearest node along with the carrier node can be identified through network access.
4. Once the nearest node is identified then this group of nodes are classified in three categories based on the timestamp using the Connectionist Temporal Classification [CTC],
    - First it classifies, timestamp of the nearest node always stays along with carrier node

- Second it classifies, timestamp of the nearest node stays greater than 3 hours and lesser than 10 hours
- Finally, timestamp of the nearest node stays in lesser time.

(iii) Wrist band monitoring system for the quarantined person

1. A thermal sensor will be deployed in the wrist band which triggers when the temperature goes high.
2. When the node tries to move over the proximity area, tracking chip in the band gives the alert message.

III MATHEMATICAL MODELLING

As we are trying to deal with the position and time spent at that position with respect to the position of the affected over the time, in order to analyze the level of the spread. This will basically lead to a series of recursive checks of position and time with respect to time continuously and at the same time avoid the uncertainty of position and time interval identification at the same time. Here we cannot use the simple network of classification algorithm to analyze the position based time intervals, hence we use the theory of Connectionist Temporal Classification [CTC] which is a type of neural network used to train the recurrent process of identification of subject based on variety of parameters at the same time which are derived from their position and time gap.

Let's take the two parameters along any axis of this directed graph based on time to be:

1. Position from the infected/active person, so let's map the input positional sequences as $X=[x1,x2,\ldots,xN]$ and $Y=[y1,y2,\ldots,yN]$ and we have to find an accurate mapping of this location as a result of their corresponding conditional probabilities:

$$Y* = Y \text{ argmax } p(Y| X)$$
$$X* = X \text{ argmax } p(X| Y)$$

2. Time spent very close to the active person would be a series of data that we will get again the corresponding conditional probability with respect to time from each time frames, hence will lead to a recursive calculation of the dependence of the factor:

$$p(\pi|x) = \pi(t=0 \to t=y)\ y(\pi t \to y),\ \forall \pi \in L\ 0$$
$$p(\pi|y) = \pi(t=0 \to t=x)\ y(\pi t \to x),\ \forall \pi \in L\ 0 .$$

Now the new directed graph will have the time delays or the feedback loops to run the recursive classification algorithm to analyze these two broad parameters with new values in every time frame and the interact with other nodes (other people coming in contact) in the target or the risk zone.

To represent a single frame CTC network, we use B to define the conditional probability of a given labelling $l \in L \leq T$ as the sum of the probabilities of all the paths corresponding to it:

$$p(l|x) = \Sigma\ \{\Pi \varepsilon B - 1\}\ p(\pi|x)$$

Now deriving it for a single set of data with both the parameter at the same time:

$$p(Y| X) = \sum \{A\varepsilon\ AxAy\} \prod \{ t\text{-}1 \to T\}\ pt(At| X)$$

Given the above formulation, the output of the classifier should be the most probable labelling for the given input pattern:

h(x) = arg max p(l|x).

h(x) ≈ B(π ∗), where π ∗ = arg max t p(π|x)

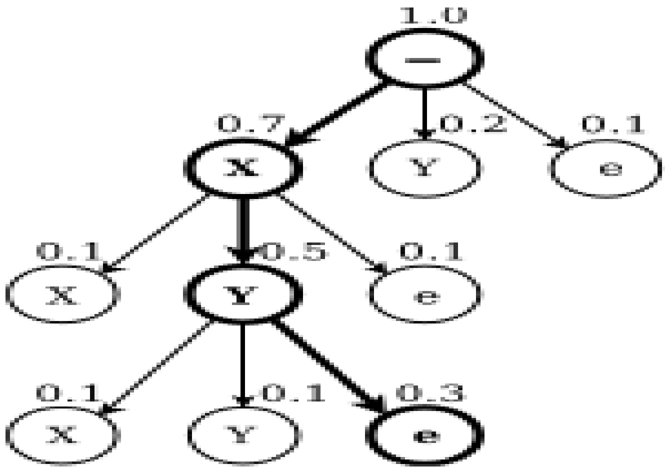

Fig2: Directed graph based on risk zone

Now, we fix the levels of riskiness based on their position (average vector length from the main subject) using their coordinates' conditional probability with respect to the time intervals such as less than 3 hours, 3 - 7 hours and more than 7 hours to determine the stage of the spread. Then we train the model to continue performing this recursively every time frame to closely monitor without losing any data. The objective function is derived from the principle of maximum likelihood. That is, minimizing it maximizes the log likelihoods of the target labels.

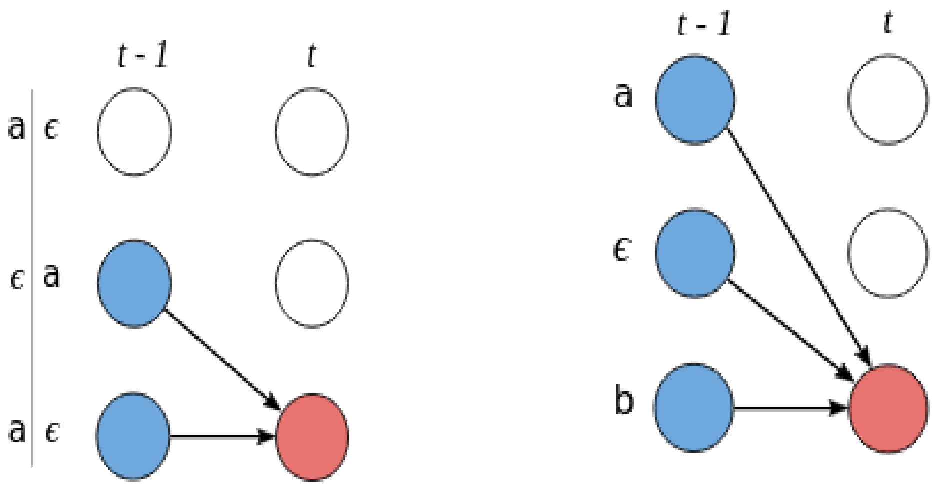

Fig3: graph based on likelihood of target labels

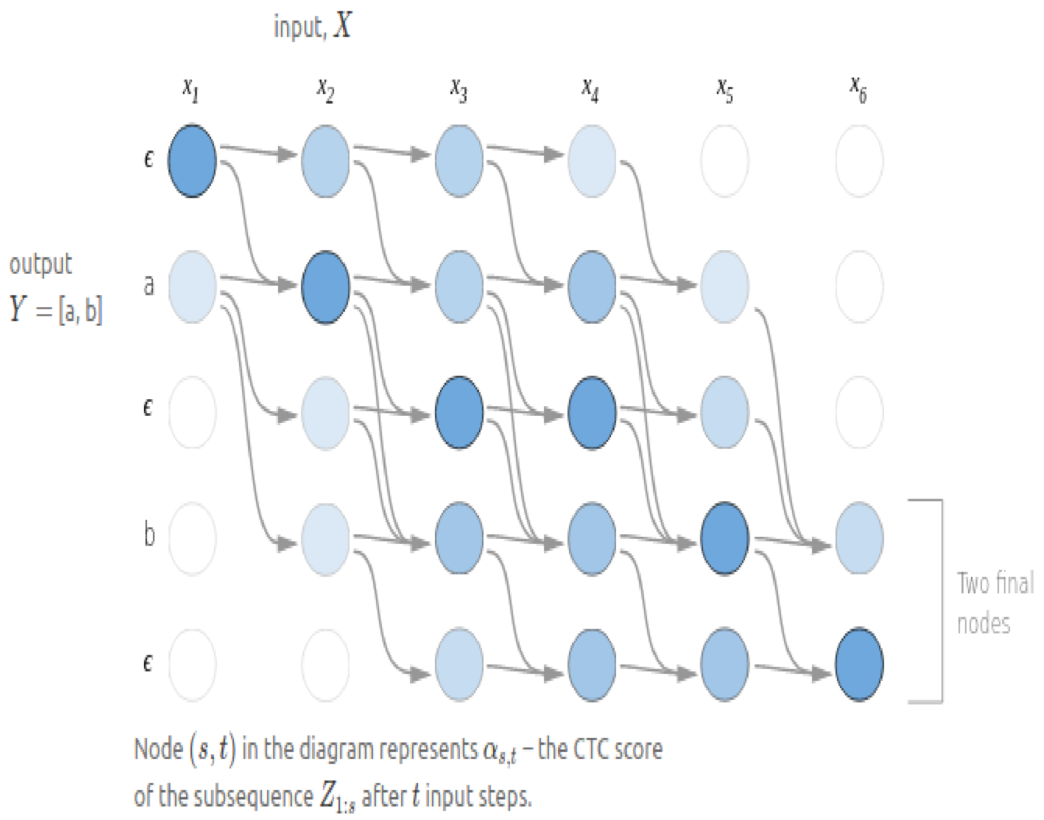

Fig 4 graph based on CTC score

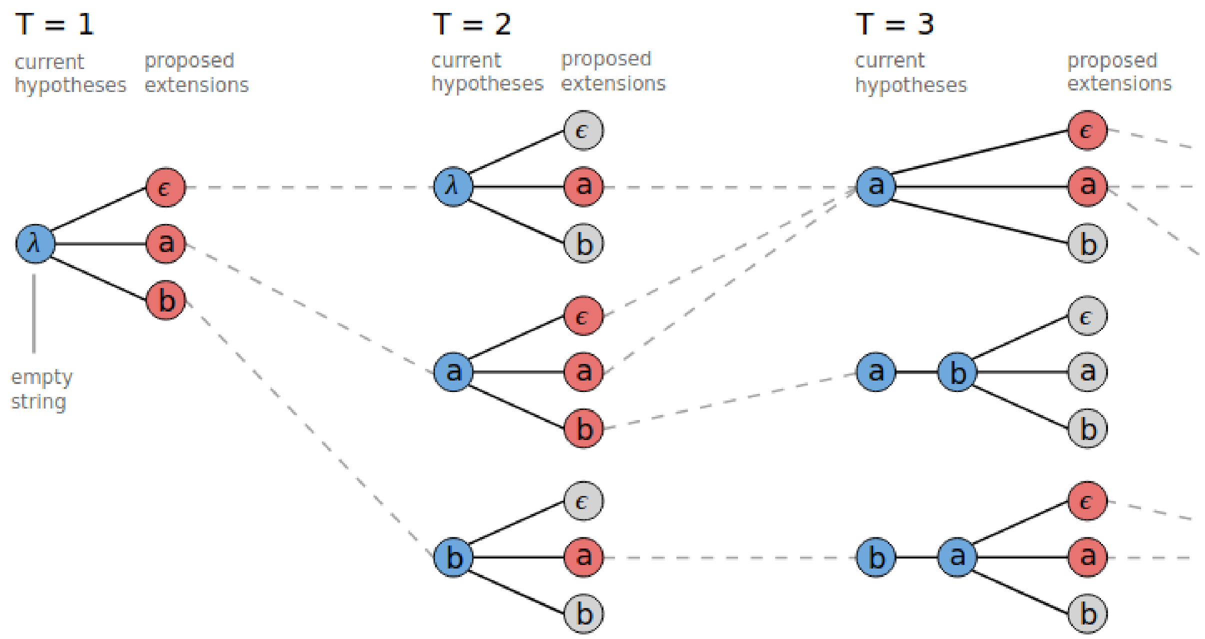

Fig5: The CTC beam search algorithm with an output alphabet {Ɛ,a,b} and a beam size of three

After the maximum likelihood training is done with the data (there is no much loss as this is CTC compared to LSTM), we can get the result in the form of graphical depiction where we will get a classified vector of various points in different levels grouped together (here we will have three levels as we have discussed above) and mostly highly affected levels' nodes will again undergo the same CTC training in a recursive manner which leads to grouping again and again, or we can also have the same graphical results in the form of a vector consisting of the conditional probability value (aggregated to a floating value) whose rise will mark the start of tracking using CTC for that particular node. And the advantage here is, since there is almost negligible loss in CTC, we can go to a higher-level tracking and analysis of the spread in real time.

V IMPLEMENTATION AND RESULTS

In this proposed system, we examined the performance of classification models for tracking and detecting of COVID-19 carriers based on various CNN models. The experimental studies were done on the models and implementation was done using CNNCTC model using the Python IDE. The results shown that our proposed model is accurate than the other studied CNN models. The measurement of performance of each classifier is measured in terms of Accuracy, Sensitivity, Specificity, False positive rate (FPR), F1 Score. In addition, this experimentation used carrier position and Time spent close to that carrier node as the CTC classifier. The results in Table 1 shows the accuracy of different classification models with mean minimum and maximum achievable models and Table 2 shows the performance measure in terms of sensitivity, FPR (false positive ratio) and F1 score. The testing and training are adopted with randomized selection with the ratio of 80:20.

The three metrics in addition to classification accuracy are commonly used in CNN models for performance evaluation. The CTC model used in the proposed system gives good accuracy compared to other CNN models.

Classification models	Mean	Minimum	Maximum
AlexNet	94.86	90.66	98.66
GoogleNet	90.73	84.00	98.66
InceptionV3	90.26	85.33	96.00
ShuffleNet	65.26	57.00	70.66
ResNet50	95.33	92.00	98.66
CTC	**96.5**	**93.2**	**98.5**

Table 1 Accuracy (%) of various Classification models based on CTC using deep features of various CNN models

Classification models	Sensitivity	FPR	F1 Score
AlexNet	94.86	3.56	94.85
GoogleNet	91.73	5.13	91.74
InceptionV3	90.26	4.86	90.28
ShuffleNet	65.26	15.36	62.79
ResNet50	94.33	3.23	93.54
CTC	**96.5**	**2.34**	**94.32**

Table 2 Performance measures (%) in terms of Sensitivity, FPR and F1 Score of different Classification models based on CTC using deep features of various CNN models

The proposed study used trained CNN models to obtain the best performance for detection of COVID-19. We evaluated the performance results of deep feature extraction based on various classification models and compared with the proposed mathematical model CNNCTC and its result shows that the model performs well compared to other models. According to the results, CNN CTC model achieved the highest classification accuracy of 96.5%.

V CONCLUSION AND FUTURE WORK

A robust and effective implementation to combat the pandemic situation is done using AI based mathematical modelling. The challenges faced in tracking and monitoring COVID-19. A GPS tracking system, geo location using Fit bit and wifi tracking modules are developed to locate the secondary infections. The calculation of real time coordinates their conditional probability with respect to time is done followed by recursive training using CTC model and classification of nodes based on risk. The proposed system CNNCTC based mathematical AI achieves an accuracy of 96.5%. In addition to this a monitoring tracking chip and thermal sensor is attached in the wrist band for complete monitoring of the COVID-19 quarantined person. Therefore, the system provides a significant solution to the pandemic outbreaks of Coronavirus. The system can be future enhanced for tracking asymptomatic person but results are positive.

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