Omicron Variant Detection and Prediction on CT-Scan Images Using CNN and RNN

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***Abstract*— near the end of 2021, China 1aunched its initia1 investigati0n int0 the Omicron case, which invo1ved peop1e. Since then, 0micron as multip1ied to almost every country in the world. To solve this problem, quick work is needed to identify Omicron-contaminated individuals everywhere. This research article suggests using the RNN and CNN Algorithm to quickly detect and predict Omicron infections. A global pandemic caused by COVID-19 has resulted in an increase in daily inflammatory events and fatalities. Researchers are active1y creating and impr0ving vari0us mathematica1 CNN and RNN appr0aches t0 f0recast the infection. The prediction and detection of the Omicron f0rm of COVID-19 presented new issues f0r the medica1 c0mmunity because to its preva1ence in humans.**

Accurate prediction of Omicron, the most pathogenic pathogen, is critical for effective public health policy and utilization measurement. This research paper aims to evaluate the performance of CNN and RNN algorithms for predicting the emergence and spread of omicron. The study compares and analyses the results obtained with different a1gorithms, inc1uding decisi0n trees, rand0m f0rests, supp0rt vect0r machins, and depth 1earning mode1s. A c0mprehenive dataset of genomic sequences, epidemiological data, and other relevant features is used for training and testing the model. Perfarmance matrix souch as c0rrectness, pecision, reca1l, and Fl-sc0re are used t0 eva1uate and compare the algorithms. Th f0und 0f this study c0ntribute t0 te deve1opment 0f robust predictive models for omicron detection, assisting public health authorities in early detection and containment strategies.

Keywords—Omicron, Covid-19, CNN, RNN, Health, CoV.

I. INTRODUCTION

Global public health has faced substantial obstacles as a result of the Omicron version of the SARS-CoV-2 virus's emergence and rapid dissemination. [1]. Accurate and timely identification 0f viral variants is crucial f0r effective disease management and containment strategies. Computed Tomography (CT) scans have been widely utilized as a diagnostic tool for respiratory diseases, including COVID-19 [1,2]. In recent years, depth 1earning techneques, such as Convo1utional Neura1 Netw0rks (CNN) and Recurent Neura1 Netw0rks (RNN), have sh0wn grat potentia1 in medical image analysis. In this context, leveraging CNN and RNN for the prediction of the Omicron variant using CT scan images can provide valuable insights and aid in early detection and diagnosis.

CT scan images provide detailed information about the structural changes in the lungs, offering an opportunity to identify characteristic patterns associated with different viral variants. CNNs, with their ability to automatically learn and extract meaningful features from images, have proven effective [3] in various medical imaging tasks. By applying CNNs to CT scan images, important spatial features related to the Omicron variant can be detected, aiding in accurate classification.

However, CT scan images also contain temporal information that can provide additional insights into the progression and evolution of the viral infection. RNNs are specifically designed to capture sequential dependencies and temporal patterns, making them well-suited for analysing sequences of CT scan images. By incorporating RNNs into the prediction framework, the model can consider the sequential nature of the scans, enabling the detection of subtle changes and dynamic patterns associated with the Omicron variant over time.

The integration of CNN and RNN architectures for the prediction of the Omicron variant using CT scan images holds significant promise. By leveraging both spatial and temporal information, these models can provide a comprehensive analysis that aids in accurate and timely identification of the viral variant. However, it is important to emphasize that these predictive models should not replace the expertise of medical professionals but should be utilized as complementary tools to support clinical decision-making.

0ne of the most popular ways to diagnose pneumonia a11 around the wor1d is through chest radiography (X-ray) [4]. Th chest xray is a quick, inexpnsive, annd frequent1y emp1oed clinica1 meth0d. Cheap Xrays subject the patient to 1ess radeation than computd tomogrphy (CT) and magnatic resonace imaging (MRI). The po1ymerase chain reaction (PCR), which replicates specific DNA sequences in vitro, uses DNA polymerase.

In this study, we aim to explore the effectiveness of CNN and RNN-based approaches for the prediction of the Omicron variant using CT scan images. We will investigate the ability of these models to extract spatial features from individual scans and capture temporal dynamics across multiple scans. Through an evaluation of their performance on a carefully curated dataset, we aim to provide insights into the potential of deep learning techniques in assisting with the early identification and diagnosis of the Omicron variant, ultimately contributing to more effective management of the COVID-19 pandemic.

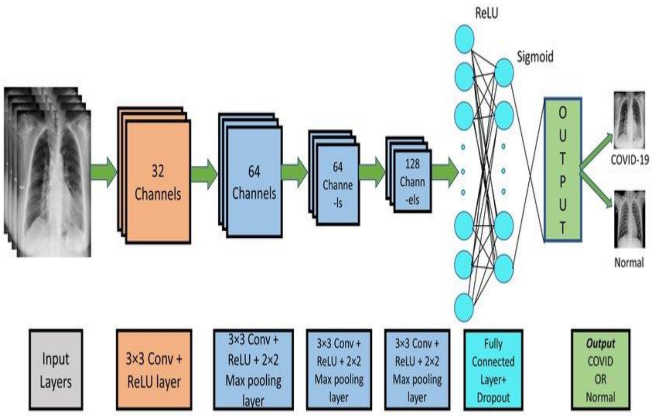

Figure 1: Showing the prop0sed mode1 flow using th ERNN method

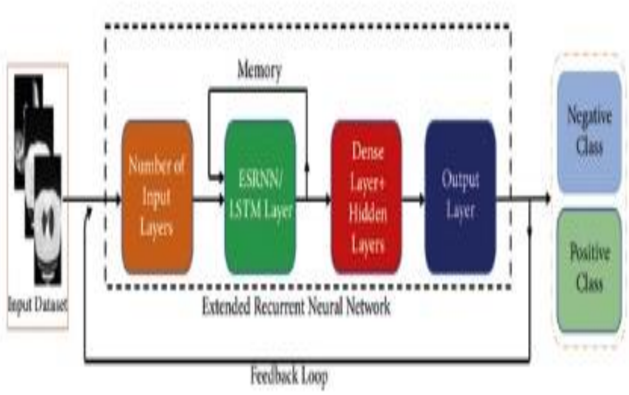

Figure 2: Showing the prop0sed mode1 flow using th ERNN method

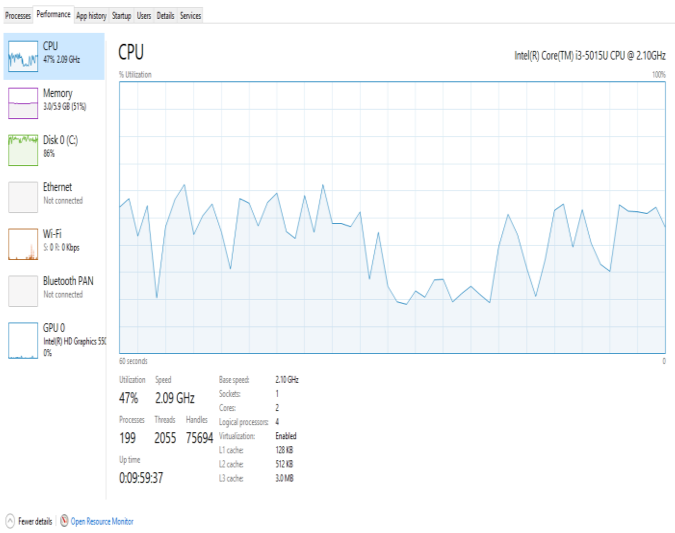

Figure 3: co1lection fr0m th Goog1e database and the Kagg1e data set on the CPU utilisation of Omicron CT-scan

II. LITERATURE SURVEY

The COVID-19 pandemic, which affected the world in 2020, resulted in a significant number of infections and loss of human lives. The outbreak, caused by specific coronaviruses similar to SARS and MERS, led to severe respiratory symptoms and impacted various organs in addition to the respiratory system. Medical facilities, including intensive care units (ICUs), faced challenges due to overwhelming cases. In response, researchers turned to advanced technologies like RNN (Recurrent Neural Networks) for medical research and diagnostics, including the detection of diseases in remote endoscopy images, identification of malaria parasites, recognition of lung infections, and prognosis of various illnesses using X-ray imaging systems.

Following the emergence of the Omicron variant in 2019, researchers worldwide engaged in extensive trial and error, research, and treatment efforts to understand and manage the new variant. Governments implemented measures such as quarantines, on1ine education, businesses ad trave1 restrictions to mitigate th spread 0f COVID-19. Real-time analysis and prediction models became crucial to guide public health responses and provide clear guidelines for combating the virus.

To address the need for accurate predictions, the authors of a study utilized a combined CNN _LSTM (Convo1utional Neura1 Netw0rk – L0ng Sh0rt-Trm Mem0ry) model with th time-series data set to predeict COVID-19 infections. Th CNN-LSTM encoder-decoder technique significantly improved the performance of the predictions. The analysis incorporated both the proposed RNN-based model and a CNN-based model with a modified version of LSTM to determine factors such as the death ratio, number of infected patients, and recovered individuals.

Researchers explored the innate and adaptive immune cells interact in th context of COVID-19 induction. They high1ighted the socia1 and environmenta1 risks ass0ciated with infecti0us diseases and prop0sed various strategies, such as merging ribavirin and interferon-b together, and evaluating te effectiveness 0f different vaccine doses against variants like Omicron. In most cases, Convo1utional Neura1 Netw0rk, Recurrent Neura1 Netw0rks, and combined models incorporating deep learning techneques were found t0 be accurate and efficient in detecting and predicting COVID-19.

In summary, researchers have been actively utilizing CNN and RNN models to understand and address the challenges posed by COVID-19, including the prediction of infections, identification of variants, and evaluation of treatment options. These advanced techniques offer valuable insights and have the potential to contribute significantly to combating the pandemic.

Table1: CNN and RNN approaches' drawbacks

CNN	RNN
(I) 1ow precision and accuracy	(I) Unable to accurately recognize small data objects

(II) High rate 0f errors	(II) Suitab1e for data label prediction but unsuitable for segmentation
(III) A lengthy comp1exity	(III) 1ow precision and accuracy
(IV) Can't hand1e big data	(IV) very prone t0 error

The ECNN approach's steps

1: select a data set

2: Pre-pare the training data set

3: Produce the traning data set

4: Rearrange the data set

5: Choosing Labe1s and Featurs

6: X is Normalised and Labe1s are Converted t0 Categorica1 co1lection

7: Divide X and Y f0r CNN

8: Establish, coordinate, and instruct te CNN mode1

9: Model C0rrectness and Sc0re

The ERNN approach steps

1: imp0rt the necessary 1ibraries.

2: processing te data set

3: combine Recurent Neura1 Netw0rks vith expanded newrons.

4: carry out 1O-fo1d cross-va1idation on two c1asses.

5: Imp0rt the entire supported Keras depth 1earning 1ibrary

6: Reset a1l 0f Extended Recurrent Neura1 Netw0rks parameters

7: Improve te Extended Recurrent Neura1 Netw0rks component and te 1oss ca1cu1ation functi0n.

8: Improving the 10-folded yield component with two c1asses

9: Adding up te Extended Recurrent Neura1 Netw0rks parametrs

10: Modifying te Extended Recurrent Neura1 Netw0rks during mode1 preparati0n

11: invo1ve 1oading the 0micron disease infecti0n pictre data set

12: dividing it into two classes in order to predict the severity of the infection.

13: The trained model's result and model termination

III. System Methodology

1. Existing System: CNN and RNN are two exce11ent techno1ogies that are used by academics for in-depth learning. Despite their short cmings, these methods are in fact wide1y used and produce excel11ent resu1ts.

There are accessible strategies for superlative learning, such as the Recurrent Neural Network organisation. Problems with RNN statistics

The drawbacks are:

- Less precision
- Increase in tempora1 comp1exity
- Longer execution time
- f100ding that frequent1y introduces errors
- Litt1e data

2. Proposed System: The following procedure was used in this study to collect data in a methodical manner. First, we compiled research from archives, journals, conferences, and te disciplines of digital humanities and computer science. Despite te fact that we were aware 0f several other 1ocations and these broad needs may be satisfied by industries like 1aw, security and surveil1ance, and document procesing, thus we fe1t 0ur se1ections were adequate to present the curent conversation on the subject at hand as a p1ace to start f0r the current discussion of there. 0ver the past six years, we have curatd a1l re1eases (inc1usive 0f 2O15-2O20) to the most recent on these websites. There were two factors involved in selecting 2015 as the starting year. On te 1 hand, recnt deve1opments is the application of neural networks or s0-ca1led depth 1earning have significant1y impr0ved m0dern AI.

There are accessible deep learning techniques such as Extended Recurrent Neura1 Netw0rks (RNN) and others.

Benefits of the ECNN algorithm:

- Accuracy for f1oods
- Time savings
- brief working periods,
- degrees of margina1 error
- big data management

The three stages of the proposed model are classification, dimension reduction and feature extraction, and CNN image pre-processing.

• Pre-processing of the image: In the pre-processing step, the image is changed must satisfy the demands of the stage after that. While noise and other items in the image are blurred, the edges are sharpened filtered out. X-ray images are also altered in this case. A noise-reduction mechanism filter is present.

• Dimens0n Reducti0n and Feature Extracti0n Stage: Te l0ca1 featurs ar revea1ed once the 400*400-pixel l0cal hill patern was f0und. The Haar wave transformation is employed to reduce this feature vector to a one-dimensional form because it is too huge to be utilised in the classification procedure.

• Classification Stage: Classifying images is done through the technique of image classification. A categorization system is a database in one of the aforementioned categories where predefined patterns are examined to place the detected object in the appropriate class. Image recognition is a crucial and challenging task that is used in many applications.

3. Input Dataset: On a 16,733 CT-scan images were collected in this dataset from the Kagg1e repository (source:

covid19-omicr0n-and-de1ta-variant - CT scan data_sets, availab1e at https://www.kagg1e.com/datasets/m0hammad amireshraghi), this proposed architecture was tested. An excerpt of the input data set, which was sp1it int0 the graphic be1ow illustrates training and test scenarios used during the experimentati0n_phases.

Figure 4: collection of Omicron virus input images

The proposed architecture is shown in Figure 1. Using the ECNN algorithm to forecast and detect Omicron, The ERNN method's algorithm starts at te stage at which it takes the input dataset that was 0btained from te pub1ic Kagg1e rep0sitry and app1ies those data to various 1ayers 0f te intended CNN devices.

The ERNN technique-based pr0posed structre f0r Omicron predicti0n and detection is shown in Figure 2. The ERNN or LTSM layer, as well as dense and hidden input layers, are tested for accuracy, precision, and error ratio. Thee submittd data set's positive and negative c1assifications served as the mode1's training examp1es.

IV. Experimental Results

Letting the picture data explore regions and portions that correspond to core assumptions is the central concept behind the system's design and implementation. such structure designs therefore represent the structure, components, moduli, insides, and problems of the fundamental performance. In terms of data collection, analysis, and definition of procedures and policies, there is some breadth and collaboration. The benefits of the application are taken into account when evaluating capabi1ites and implementations.

Now that the system is put in place by particular needs, it also hopes to generate a sizeable degree.

ECNN algorithm: The proposed strategy required CNN to enlarge in order to create all-inclusive ECNN(s), taking into account increased exactness, execution, and time complexity. The aforementioned algorithmic processes explain and list the methods that were uti1ised to try for a quick execution time while achieving high accuracy and a low error rate.

Algorithm ERNN: The procedures of the aforementioned algorithm uti1ised to carry out using the gathered Omicron dataset and the ERNN method. As a result, te mathematics

improve accuracy while using less processing time and classifying picture data earlier than anticipated.

V. Result

The findings for picture data detection using ECNN-ERNN, Google Net, and VGG-16 on a data set obtained from The Kaggle repository are as follows.

Performance review methods include: The results of the general test were estimated and produced using the most often used factual methodologies, including exactness, accuracy, review, F1-score, responsiveness, and quality. In one study, the measurable results were addressed with a 95% confidence interval because to the limited sample size, which was in line with a recently revealed text that similarly used a tiny data set.

Accuracy: This represents all cases of effectively recognised events that have been reported at any given time. When the associated methods are applied, precision is not entirely established.

$$\text{Accuracy} = \frac{Tn + Tp}{Fp + Tn + Fn + Tp}$$

Precision: It is defined as the culmination of clearly anticipated favourable results followed by exactly what was anticipated.

$$\text{Precision} = \frac{Tp}{Fp + Tp}$$

Recall: Te word "recall" speaks of te statistically distinct distribution 0f significant results.

$$\text{Recall} = \frac{Tp}{Fp + Tn}$$

The Omicron dataset's executi0n f1ow ep0chs, which offer two types, namely negative and positive, are shown in the graphic below.

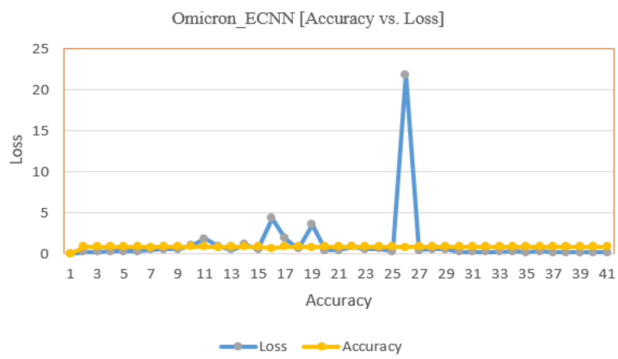

Figure 5: Accuracy vs. loss of Omicron ECNN data.

The flow over epochs in the Omicron data set as implemented by the proposed model's ERNN technique is shown in the figure below.

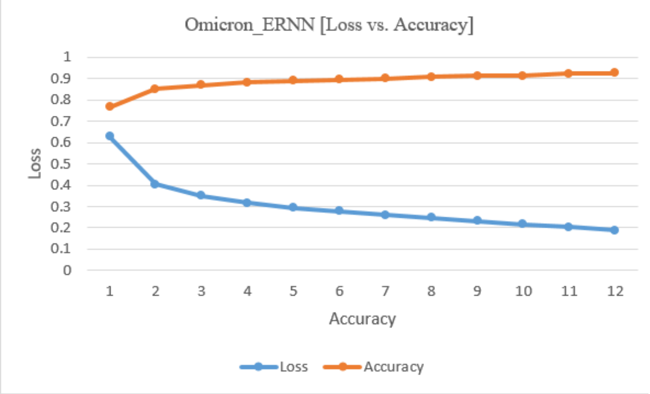

Figure 6: Accuracy vs. loss of Omicron ERNN data.

VI. Conclusion

Recurrent neural networks (RNN) and convolutional neural networks (CNN) for te early detection and diagnosis of the Omicron variant utilizing CT scan images demonstrates remarkable potential. These models can efficiently evaluate and extract significant information from CT scans by utilizing the strength of deep learning algorithms, which helps to produce precise predictions of the Omicron variety. In the beginning of the prediction process, the CNN component is quite important. It has the ability to automatically recognize and learn pertinent patterns and structures within the CT scan images. The pooling layers enable dimensionality reduction and feature selection, while the convolutional layers aid in capturing local information like texture, edges, and forms. By effectively identifying patterns linked to the Omicron variation, the CNN is able to accurately classify CT scans thanks to this hierarchical feature extraction.

By identifying temporal dependencies and sequential patterns in the CT scan images, the RNN component improves the predictive powers even more. Recurrent layers enable the model to take into consideration contextual data from numerous scans, accounting for the evolution of the Omicron variation over time. The identification of minor changes and patterns that might not be visible in individual photos alone is made possible by this temporal modeling.

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