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Research Article

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Omicron Virus Data Analytics Using Extended RNN Technique

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Abstract
The OMICRON case that tainted human beings become first observed in China towards the end of 2021. From that point, OMICRON has spread practically all nations on the planet. To conquer this issue, it requires a fast work to recognize people tainted with OMICRON all the more rapidly. This research article proposes that RNN techniques to be utilized for rapid detection and predicting of OMICRON infections. RNN is finished utilizing the Elman agency and implemented to the OMICRON dataset gathered from Kaggle. The dataset accommodates of 75% preparing information and 25% analyzing information. The learning boundaries utilized were the most extreme age, secret hubs, and late learning. Results are for this exploration results show the level of precision is 88.28. Oddity is one of the elective conclusions for potential OMICRON illness is Recurrent Neural Network (RNN).

Keywords: Omicron Disease, Cross-Validation Methods, Classification Algorithms, Disease Prediction, RNN, Data minelaying, Feature Selection, Data Pre-processing.

Introduction

The COVID-19 was declared as global pandemic by the World Health Organization (WHO) in March 2020. The OMICRON is one of the mutant viruses of COVID-19 disease. The OMICRON is known as respiratory illness, which can undoubtedly infect individuals through the air and physical (actual) contact. Hack, windedness, loss of taste and/or smell, mild and/or high fever, cerebral pain, and muscle throb become the most well known side effects [1-3]. The infection acquires a huge effect in different life field [4]. The circumstances demonstrate that the OMICRON turns into a basic issue to settle soon. The affirmed instance of OMICRON contacts 138416498 individuals, 2975875 demise cases, and in 192 nations. This number is still growing day by day (today). Lessening the tempo of contamination improvement is one of the endeavors which can be constantly being made. The contamination with speedy transmission likewise requires fast survive. The utmost utilized strategies in contradiction of the infection propagate are finding, testing, isolation, detachment, and medication [4, 5]. In any case, of OMICRON affirmation, for example, Reverse Transcription PCR (RT-PCR) is yet not so effective to address and cover the infection spread [6]. Computerized reasoning such as use of Artificial Intelligence turns into an anticipating tactic that should further develop the detecting strategy [7-12]. The faster the identity of anthropological tainted through OMICRON; the faster remedy may be applied. It thoroughly can be probable the high-quality effort to decrease the tempo of development. In this way, an elective framework in early conclusion for people tainted by OMICRON is required. One of the alternatives is the Recurrent Neural Network (RNN) that's a part of Artificial Neural Network model. Artificial Neural Network (ANN) is an execution of synthetic brainpower innovation that addresses the cerebrum of individuals who normally try to reproduce the academic experience within side the people's brain [4]. Recurrent NN (RNN) is a sort of fake brain system, which have a primary structure of rehashing tiny cells. Intermittent micro cells are framed and arranged with historical data to study original data [13].

Literature Survey

Profound erudition has exposed a sensational expansion in clinical psychology through overall and explicitly into clinical x-ray-based conclusion. Profound erudition models achieved unmistakably computer imaginative and prescient issues associated with scientific picture analysis. Artificial NNs (ANNs) beat added regular systems and procedures of clinical image investigation [7, 8]. Because of its exceptionally encouraging outcomes given by RNNs in clinical picture examination and grouping, they are considered as recognized norm in this area [9, 10]. RNN has been applied for an collection of order assignments linked with medical analysis, for example, remote endoscopy images [13], discovery of malarial parasite in images of tiny blood smear [11], lung infection [10], mammary gland cancers recognition [12], interstitial lung illness [14], CAD-primarily based totally prognosis in chest radiography [15], dedication of pores and skin malignant increase via way of means of characterization [16], and programmed locating of various chest illnesses utilizing chest X-beam photo arrangement [17]. Subsequently the development of the OMICRON in 2019, many analysts remain locked in the trial & error and exploration exercises connected with analysis, treatment, and the executives of OMICRON. Scientists in [18] have detailed the meaning of the relevance of AI techniques in picture examination of the discovery and the board of OMICRON cases. Coronavirus identification should be possible precisely utilizing profound erudition model's investigation for pneumonic Computed Tomography (CT) [18]. Scientists [19] have planned an opensource OMICRON determination framework in view of a profound RNN. In this review, customized profound RNN configuration has been accounted for the identification of OMICRON patients utilizing X-beam pictures. One more huge review has investigated the X-beam dataset involving X-beam pictures having a place with normal pneumonia patients, OMICRON patients, and individuals with no disease [20]. We concentrate on involvement of the best-in-class RNN structures for the programmed recognition of patients with OMICRON. Move learning has accomplished a promising precision of 97.82% in OMICRON location in this review. One more late and applicable review is been led on approval and flexibility of Decay, Transmission, and Combine-type profound RNN of OMICRON discovery utilizing chest X-beam picture grouping [21] creators have announced the aftereffects of the review with a precision of 95.12%, responsiveness of 97.91%, and explicitness of 91.87%. [3].

Methodology

Existing System

There are approachable in superficial learning strategies, for example, the Recurrent Neural Network organization and intermittent neural organization. RNN computation Drawbacks: The disservices are:

- Little precision
- In flood Time Complexity
- In flood Executing Time
- In flood Fault prone
- Minor Data Size

Computation downside:

- Little precision
- In flood Time Complexity
- In flood Execution Time
- In flood Fault prone
- Little Data Size

Proposed System

There are available in deep learning method like Extended Recurrent Neural Networks (RNN) i.e., in Deep Learning Technique. ECNN algorithm Advantages:

- In flood precision
- Fewer time consumption
- Little Performance Time
- Little Mistake Degree
- Big Data Scope

Results

Basic idea of the execution is to assure that the Omicron disease severer affected role collected statistics functioned in the way that can compel preparation, subdivision from their first outlook.

ERNN Algorithm

Recurrent NNs (RNN) is foremost used techniques of Artificial NN (ANN) systems. It is a kind of organization of brain systems where it has circles as input associations. The Elman Network preparing design is as like as the Multi-Layer Perceptron (MLP) preparing, the establishment yield contrasted with the goal end result and mistake is applied to refresh the company hundreds as indicated with the aid of using the Backpropagation mistake calculation with the unique case that the upsides of affiliation hundreds are consistent for 1.0. The prototypical of the Elman network explained below as in Equation 1.

$$y = \sum_{k=1}^{p} v_k \frac{1}{1+\exp^{-(\sum_{i=1}^{n} x_i w_{ik(a)} + \sum_{j=1}^{p} u_j w_{jk(b)} + b_k)}} + b_0 + \varepsilon \qquad (1)$$

Algorithm

ERNN [12] is one of the most used classes of Neural Networks (NN). Its Arrangement Labeling-Part of discourse named element acknowledgment and labeling are extremely useful and effective to obtain desired results. To infer the mentioned advantages, we trundled out positive enhancements to Recurrent NN (traditional) and get ERNN; by making a group [13], [14] of changes:

Step 1: Drafts the degree of put-away records from experience.
Step 2: Drafts the quantity of data being added in the existing implementation.
Step 3: Drafts the amount of the yield evidence existence

Our experiment involved the following related processes:
Step 1: Introduce the essential collection
Step 2: Introduce the research dataset
Step 3: Implement in the floodlight ordering of the change of evidence
Step 4: Prepare the data composition with 70-time phases and 2 yield
Step 5: Introduce Keras deep learning library
Step 6: Reset of the ERNN
Step 7: Enhancement of the ERNN part & about regulation of loss calculation function.

Step 8: Improvement of yield chunk.
Step 9: Accelerate the ERNN
Step 10: Fitting the ERNN in the research dataset
Step 11: Load the Omicron disease infection test image data for 2020
Step 12: Become an expected Omicron disease infection in Dec 2019
Step 13: Imagine aftereffects with anticipated or genuine Omicron disease infection

Input Dataset

Here the input dataset is having 14 columns with target class, i.e., severity level of the Omicron disease.

Research Data (Input)

The research dataset collected from various opensource resources such as Kaggle had 6098 x-ray images.

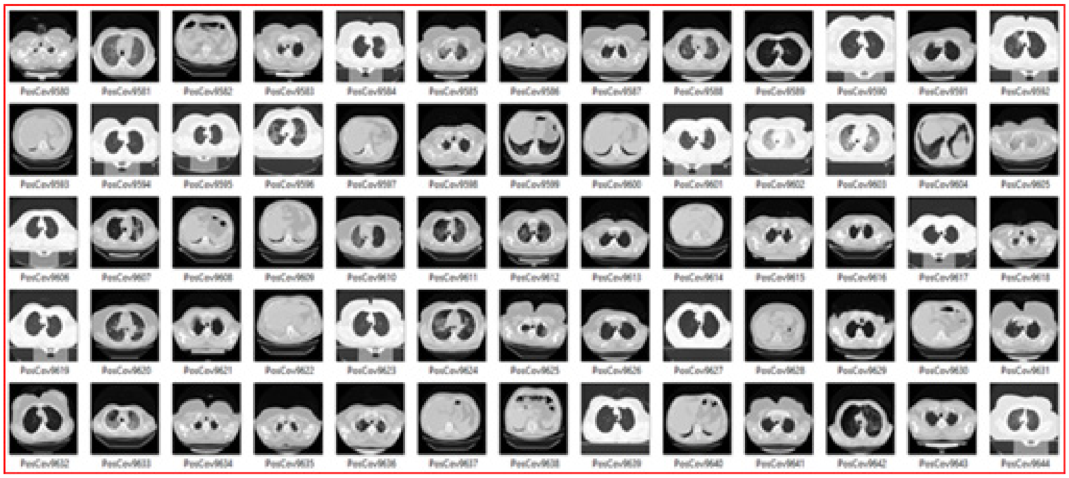

Figure 4.1: Input dataset, i.e., Omicron disease dataset of Proposed System

Results

Here are the result of in finding Omicron disease detection by integrating ERNN.

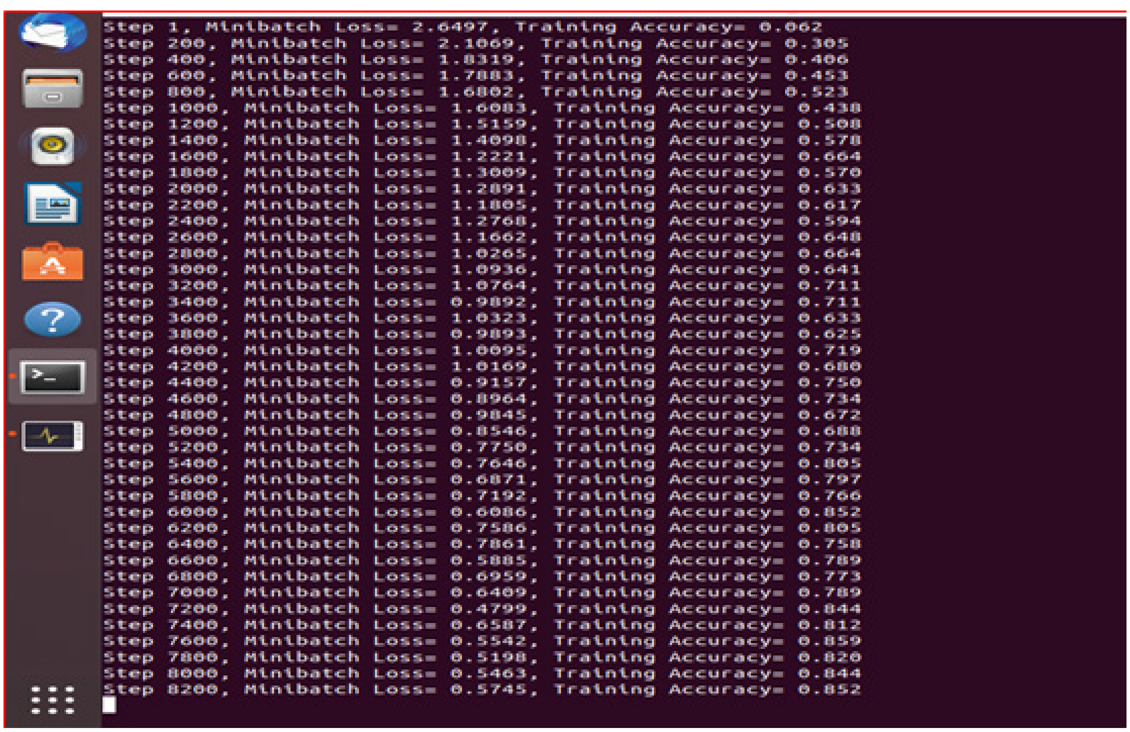

Figure 5.1: The Execution flow of ERNN

Fig 5.1 Exemplify the execution flow through Epochs on Omicron dataset

Figure: 5.2 Computing resources occupancy in the execution process of ERNN

Fig 5.2 Exposes the CPU, RAM, and other computing resources occupancy of Omicron ERNN code.

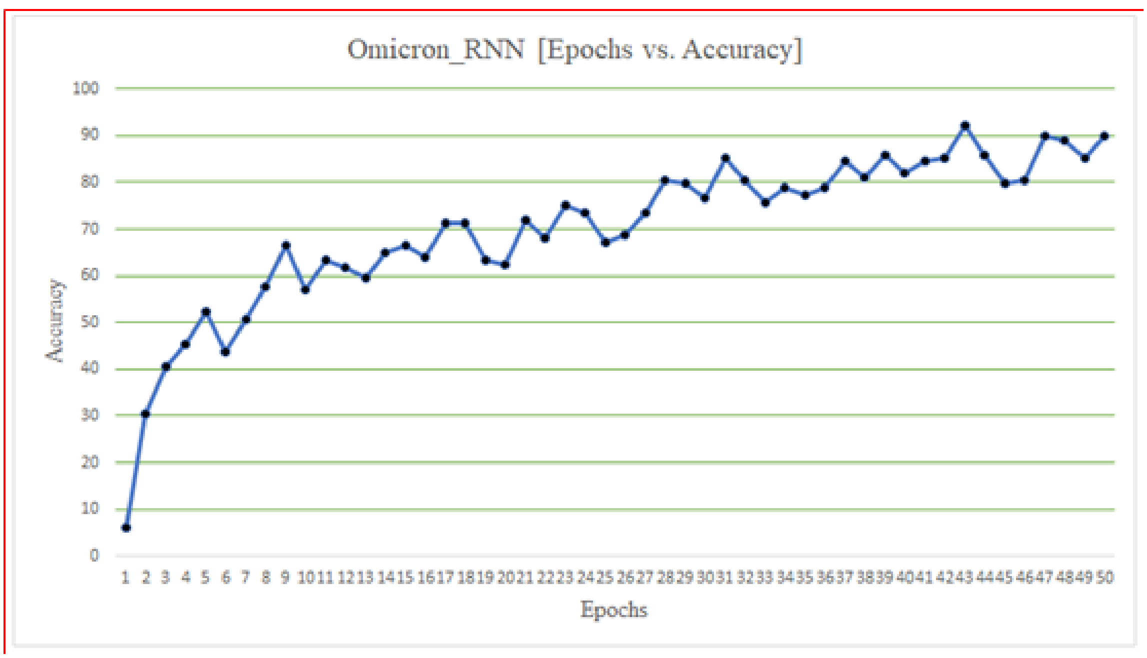

Figure 5.3: Omicron RNN results chart comparing Epochs vs. Accuracy

Fig 5.3 Demonstrates the accurateness of the code through Epochs vs. Accuracy graph representation.

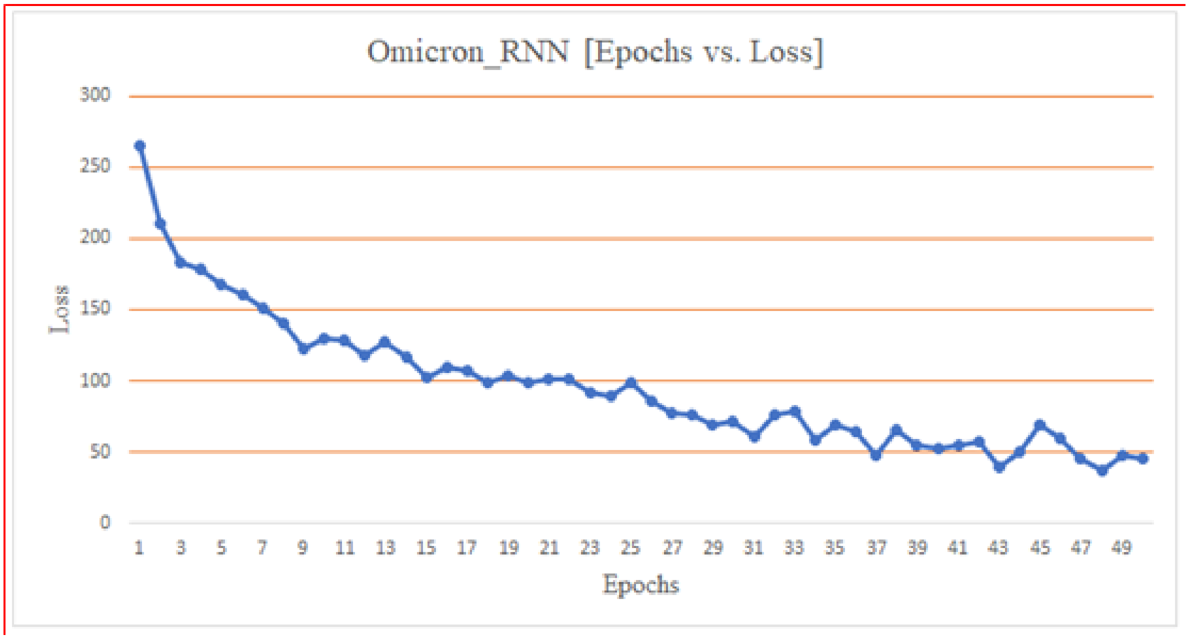

Figure 5.4 Omicron RNN results graph comparison of Epochs vs. Loss

Fig 5.4 Exemplifies the reduction ratio of the loss compared with epochs during RNN code execution on Omicron dataset taken from Kaggle.

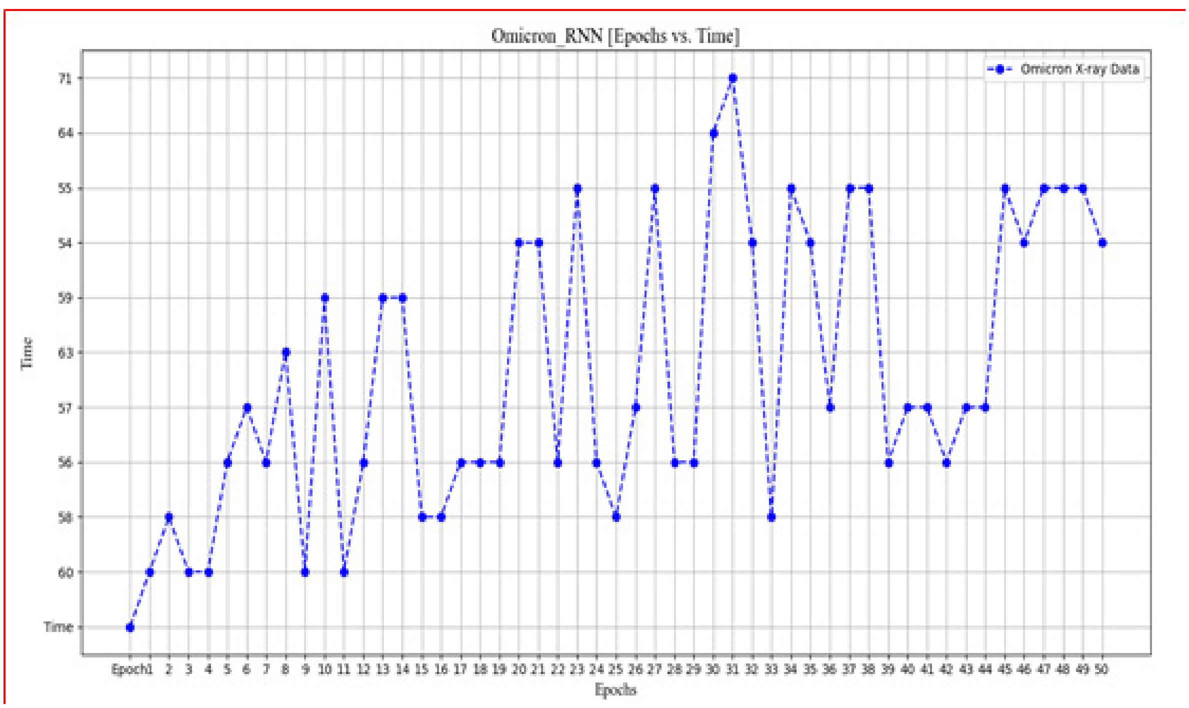

Figure 5.5: Omicron code execution Time consumption comparison with respect to Epochs

Fig 5.5 Depicts the time frequency to complete each iteration of Omicron RNN code execution with respect to each epoch.

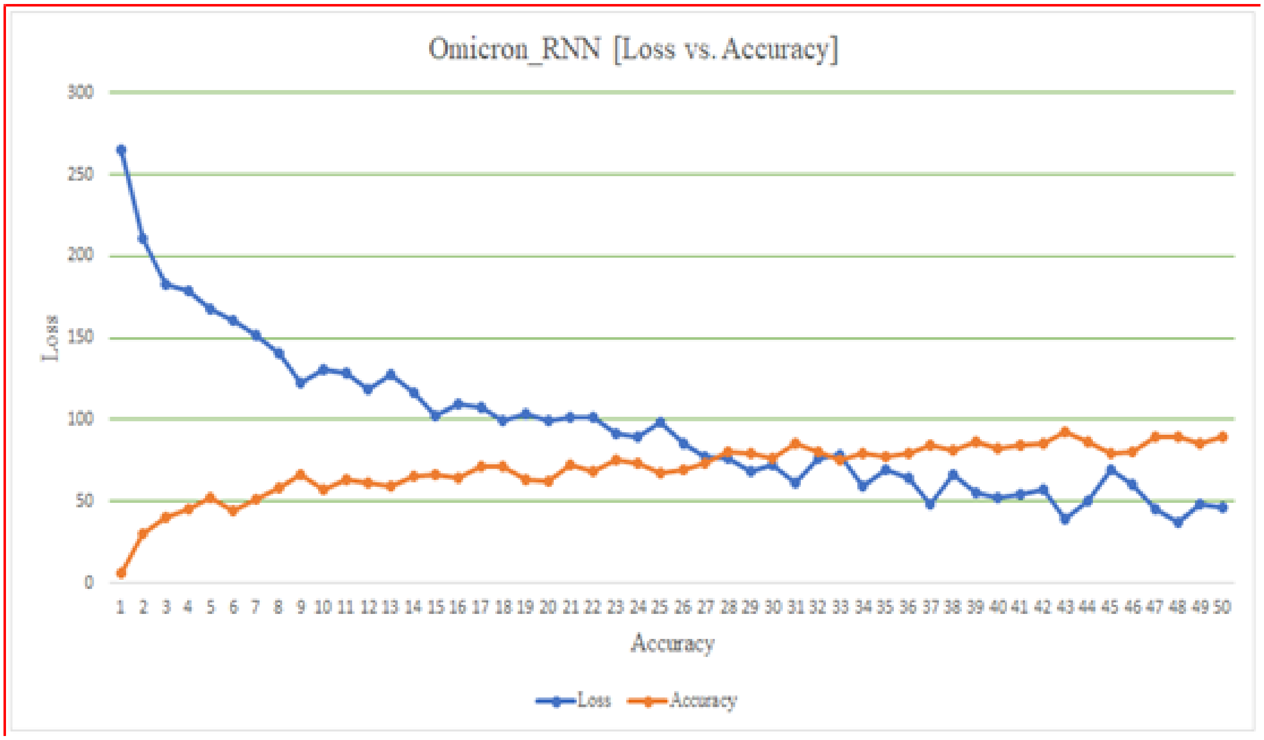

Figure 5.6: Omicron RNN Loss vs. Accuracy results graph

Fig 5.6 The above image explains and compares the Loss with respect to Accuracy of Omicron RNN code execution on database.

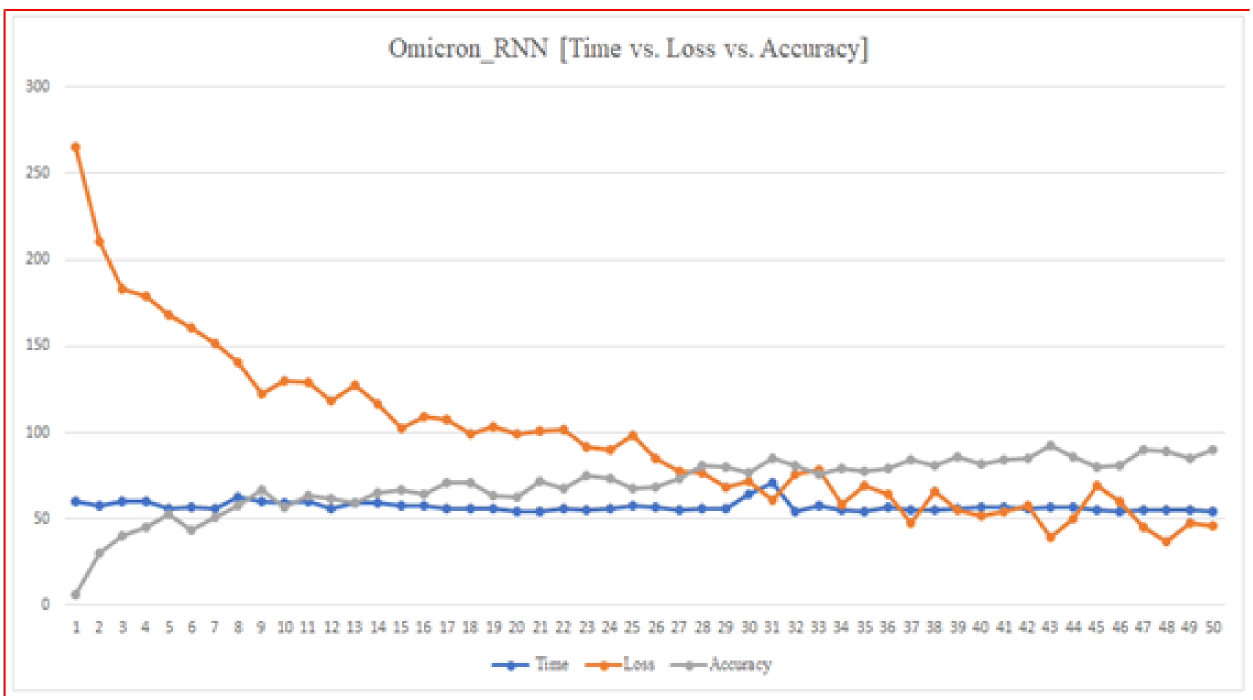

Figure 5.7: Omicron RNN graph representing Time vs. Loss vs. Accuracy frequency

Fig 5.7 Explains how the Loss is reduced with respect to time and accuracy on each epoch.

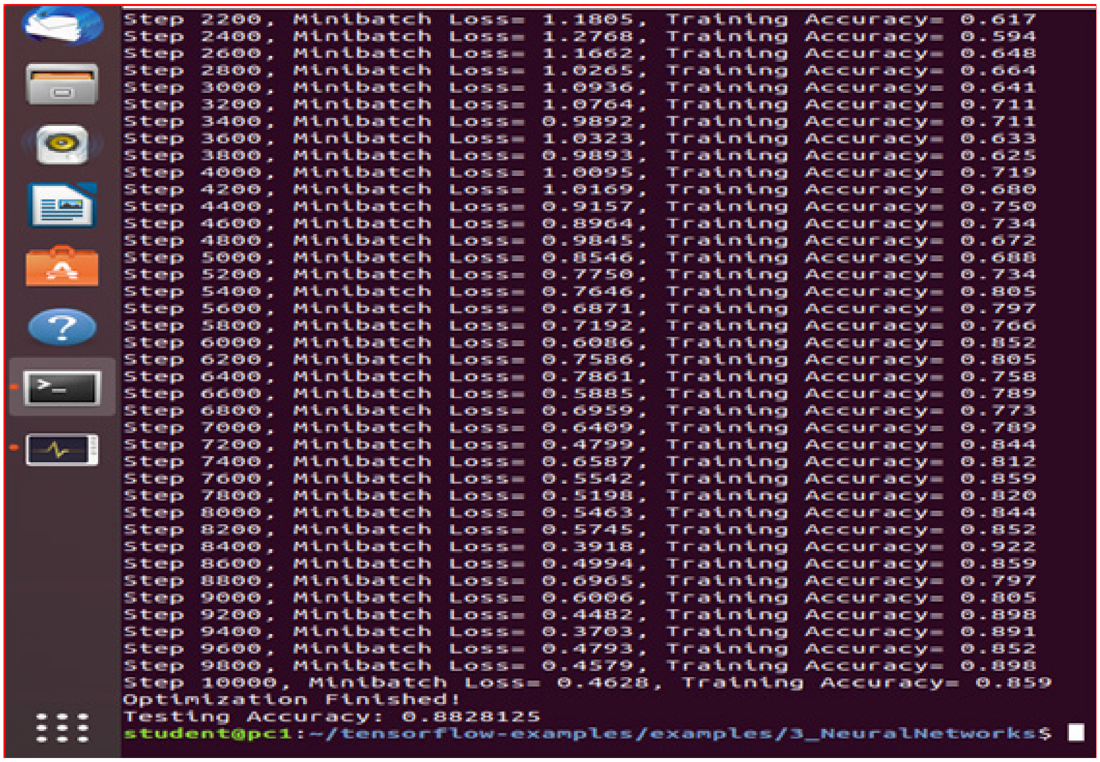

Figure 5.7: Omicron RNN graph representing Time vs. Loss vs. Accuracy frequency

Fig 5.8 The Omicron RNN code achieved the accuracy of 88.28% during training of the module.

Evaluation Methods

The following are measurements of evaluation methods or metrics.

$$Quality = \frac{BP + VM}{BP + VP + BM + VM}$$

$$Preciseness = \frac{BP}{BP + VP}$$

$$Callback = \frac{BP}{BP + VM}$$

$$F - measure = \frac{2xPrecisenessxCallback}{Preciseness + Callback}$$

Conclusions

The strategy proposed in this exploration is to anticipate OMICRON with 12 symptoms by altering the erudition boundary of Recurrent NN (RNN) to find an ideal boundary. Later in the preparation stage, the erudition frequency, stowed away layer, and most extreme age boundaries produced ideal incentive aimed at constructing the greatest prototypical of Recurrent NN. The qualities stand 0.3 aimed at the erudition rate, 6 aimed at the secret layer, and 6098 for the most extreme age. Through executing ideal boundary standards, the best precision esteem created is 88.28%. The exactness created by the system demonstrate the way that Recurrent NN can be the best option for analyzing OMICRON. The future exploration is trusted that exactness produced for analyzing OMICRON remains superior to it.

References

1. Alamsyah, A., Prasetiyo, B., Al Hakim, M. F., & Pradana, F. D. (2021). Prediction of COVID-19 Using Recurrent Neural Network Model. Scientific Journal of Informatics, 8(1), 98-103.
2. Alazab, M., Awajan, A., Mesleh, A., Abraham, A., Jatana, V., & Alhyari, S. (2020). COVID-19 prediction and detection using deep learning. International Journal of Computer Information Systems and Industrial Management Applications, 12(June), 168-181.
3. Maghded, H. S., Ghafoor, K. Z., Sadiq, A. S., Curran, K., Rawat, D. B., & Rabie, K. (2020, August). A novel AI-enabled framework to diagnose coronavirus COVID-19 using smartphone embedded sensors: design study. In 2020 IEEE 21st International Conference on Information Reuse and Integration for Data Science (IRI) (pp. 180-187). IEEE.
4. Chamola, V., Hassija, V., Gupta, V., & Guizani, M. (2020). A comprehensive review of the COVID-19 pandemic and the role of IoT, drones, AI, blockchain, and 5G in managing its impact. Ieee access, 8, 90225-90265.
5. Varela-Santos, S., & Melin, P. (2021). A new approach for classifying coronavirus COVID-19 based on its manifestation on chest X-rays using texture features and neural networks. Information sciences, 545, 403-414.
6. Alamsyah, A., Prasetiyo, B., Al Hakim, M. F., & Pradana, F. D. (2021). Prediction of COVID-19 Using Recurrent Neural Network Model. Scientific Journal of Informatics, 8(1), 98-103.

7. Imran, A., Posokhova, I., Qureshi, H. N., Masood, U., Riaz, M. S., Ali, K., ... & Nabeel, M. (2020). AI4COVID-19: AI enabled preliminary diagnosis for COVID-19 from cough samples via an app. Informatics in Medicine Unlocked, 20, 100378.
8. Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021). An intelligent framework using disruptive technologies for COVID-19 analysis. Technological Forecasting and Social Change, 163, 120431.
9. Rasheed, J., Jamil, A., Hameed, A. A., Aftab, U., Aftab, J., Shah, S. A., & Draheim, D. (2020). A survey on artificial intelligence approaches in supporting frontline workers and decision makers for the COVID-19 pandemic. Chaos, Solitons & Fractals, 141, 110337.
10. Albahri, O. S., Zaidan, A. A., Albahri, A. S., Zaidan, B. B., Abdulkareem, K. H., Al-Qaysi, Z. T., ... & Rashid, N. A. (2020). Systematic review of artificial intelligence techniques in the detection and classification of COVID-19 medical images in terms of evaluation and benchmarking: Taxonomy analysis, challenges, future solutions and methodological aspects. Journal of infection and public health, 13(10), 1381-1396.
11. Chowdhury, M. E., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M. A., Mahbub, Z. B., ... & Islam, M. T. (2020). Can AI help in screening viral and COVID-19 pneumonia?. IEEE Access, 8, 132665-132676.
12. Rashid, M. T., & Wang, D. (2021). CovidSens: a vision on reliable social sensing for COVID-19. Artificial intelligence review, 54(1), 1-25.
13. Shuja, J., Alanazi, E., Alasmary, W., & Alashaikh, A. (2021). COVID-19 open source data sets: a comprehensive survey. Applied Intelligence, 51(3), 1296-1325.
14. Cheng, F., Desai, R. J., Handy, D. E., Wang, R., Schneeweiss, S., Barabási, A. L., & Loscalzo, J. (2018). Network-based approach to prediction and population-based validation of in silico drug repurposing. Nature communications, 9(1), 1-12.
15. Prasetiyo, B., & Muslim, M. A. (2019, October). Analysis of building energy efficiency dataset using naive bayes classification classifier. In Journal of Physics: Conference Series (Vol. 1321, No. 3, p. 032016). IOP Publishing.
16. Walid, A., & Alamsyah, I. U. (2017). Recurrent neural network for forecasting time series with long memory pattern. In J. Phys.: Conf. Ser (Vol. 824, No. 1, p. 012038).
17. Muslim, M. A., Kurniawati, I. I. N., & Sugiharti, E. (2015). EXPERT SYSTEM DIAGNOSIS CHRONIC KIDNEY DISEASE BASED ON MAMDANI FUZZY INFERENCE SYSTEM. Journal of Theoretical & Applied Information Technology, 78(1).
18. Mishra, M., Parashar, V., & Shimpi, R. (2020, September). Development and evaluation of an AI System for early detection of Covid-19 pneumonia using X-ray (Student Consortium). In 2020 IEEE Sixth International Conference on Multimedia Big Data (BigMM) (pp. 292-296). IEEE.
19. Vinod, D. N., & Prabaharan, S. R. S. (2020). Data science and the role of Artificial Intelligence in achieving the fast diagnosis of Covid-19. Chaos, Solitons & Fractals, 140, 110182.
20. Hammoudi, K., Benhabiles, H., Melkemi, M., Dornaika, F., Arganda-Carreras, I., Collard, D., & Scherpereel, A. (2021). Deep learning on chest X-ray images to detect and evaluate pneumonia cases at the era of COVID-19. Journal of medical systems, 45(7), 1-10.
21. Ahmad, M., Tundjungsari, V., Widianti, D., Amalia, P., & Rachmawati, U. A. (2017, November). Diagnostic decision support system of chronic kidney disease using support vector machine. In 2017 second international conference on informatics and computing (ICIC) (pp. 1-4). IEEE.
22. shensheng Xu, S., Mak, M. W., & Cheung, C. C. (2017, July). Deep neural networks versus support vector machines for ECG arrhythmia classification. In 2017 IEEE International Conference on Multimedia & Expo Workshops (ICMEW) (pp. 127-132). IEEE.
23. Dansana, D., Kumar, R., Bhattacharjee, A., Hemanth, D. J., Gupta, D., Khanna, A., & Castillo, O. (2020). Early diagnosis of COVID-19-affected patients based on X-ray and computed tomography images using deep learning algorithm. Soft Computing, 1-9.

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