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MACHINE LEARNING ALGORITHMS FOR COVID-19 DETECTION

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Abstract: This study compares Machine Learning techniques like Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Deep Learning for COVID-19 detection. It presents a comprehensive comparative analysis of these three distinct approaches in the context of COVID-19 detection, without limiting the scope to a specific data source as well as assesses the performance, accuracy, precision, recall, and F1-score of these models across various datasets and types, revealing their strengths and weaknesses. The findings provide insights into their suitability for different applications, offering guidance for researchers and practitioners in improving COVID-19 diagnostics and monitoring.

I. INTRODUCTION

The COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, has brought unprecedented challenges to global healthcare systems, economies, and societies. Rapid and accurate detection of COVID-19 cases is crucial for timely patient care, disease control, and public health management [1,2,3]. In this context, machine learning techniques have emerged as powerful tools for automated COVID-19 detection, offering the potential to augment traditional diagnostic methods and streamline the testing process.

Artificial intelligence (AI) and machine learning algorithms, particularly Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Transfer Learning models, have gained attention for their ability to analyse and interpret complex datasets. These algorithms have demonstrated promising results in a wide range of applications, including computer vision, natural language processing, and medical image analysis. In the specific context of COVID-19, they hold the promise of accurate, efficient, and scalable detection [1,2,3].

This paper presents a comprehensive comparative study that aims to evaluate and contrast the performance of ANN, CNN, and Transfer Learning models in the task of COVID-19 detection. The significance of this research lies in its potential to inform the selection of appropriate machine learning approaches for different scenarios and data types, thus aiding in the development of effective COVID-19 diagnostic systems. The Artificial Neural Network (ANN) is used for early coronavirus prediction due to its ability to handle complex, non-linear problems. ANN generates a relationship function with provided data, addressing the issue of multiple factors and uncertainty [1]. COVID-19 detection can be achieved through a classification approach based on chest x-rays, using deep learning and massive annotated medical image datasets. CNN could recognize patterns with extreme variability and robustness to distortions and geometric transformations, eliminating the need for manual feature extraction [3-6]. It had been developed as a time-efficient method for diagnosing COVID-19, replacing RT-PCR due to its limited accessibility and time-consuming nature.

II. Literature Review

Machine learning and AI are crucial tools in diagnostics, enhancing traditional methods and providing rapid, data-driven insights. Recent studies have demonstrated the possibility of detecting COVID-19 by listening for the sound of coughing. On the pilot DiCOVA dataset, a machine learning-based approach published in [7] that used locally produced features and an SVM model was able to attain an AUC score of 85.02 [4]. Another of these works used a deep convolutional neural network (DCNN) for splitting a chest CT image. Here, a feature variation block that modifies the features' global parameters to segment COVID-19 infection was introduced [8]. Another work for COVID-19 detection created a model for X-ray, ultrasound, and CT images and compared the performances of several deep learning models [3]. Another paper had introduced an ANN network with six neurons in input layer, five in output layer and ten into the hidden layer to detect Covid in patients with asymptotic symptoms [1].

III. DATA COLLECTION AND PREPROCESSING

This manual covers data collection, preparation, and missing data preprocessing procedures for modern analytics, machine learning, and data-driven decision-making, ensuring useful and trustworthy data. Data sources include clinical data, epidemiological information, and genomic data. Clinical data, gathered in healthcare facilities, provides detailed medical information like diagnoses, prognoses, and outcomes [1]. Epidemiological information, focusing on disease prevalence and causes, is essential for research and policy-making in public health [1]. Genomic data, including DNA sequences and variations, is crucial for understanding the genetic basis of diseases and conducting genetic studies [1]. In order to improve model performance and shorten computation time, data cleaning entails finding and fixing errors and discrepancies, filling in blanks with methods like imputation, deletion, or flagging, and identifying pertinent features for feature selection. The choice of features can be directed by techniques like feature importance analysis, correlation analysis, and domain knowledge [1-5]. Scaling features to a reliable range is achieved through normalization methods like Z-score standardization and Min-Max scaling, preventing features with different units or scales from influencing the analysis. Machine learning techniques often require categorical data to be encoded in numerical form using techniques like one-hot encoding and label encoding. Data transformation is necessary for each analysis or modelling technique. Handling missing data is crucial for machine learning algorithms, and methods include deletion, imputation, interpolation, flagging, creating missing data indicators, and utilizing expert knowledge for accurate inference.

IV. METHODOLOGY

CNN for Diagnosis:

The proposed deep convolutional neural network (CNN) design for diagnosing chest X-ray (CXR) images. The model consists of 5 blocks, each containing depth-separable convolution layers, pointwise convolutions, and maxpool layers to reduce spatial dimensions. This design reduces computation costs and model parameters, leading to faster processing and improved accuracy, while also fitting the data distribution.

The dataset used for the experiment includes CXR scans from individuals with pneumonia, COVID-19, and other illnesses. COVID-19 CXR scans are collected from various sources, resulting in a total of 4,273 CXR images from patients with pneumonia and 1,583 scans from healthy individuals. The dataset is divided into three classes, with 1,330 images in each class to create a balanced dataset.

Table I summary of proposed CNN Architecture

Block	Layer Type	Stride	Kernel-size	Output Size	Parameters
Input	Input Layer	2	-	128x128x3	0
	Conv2D	2	3x3	64x64x16	448
	Batch-Normalization	-	-	-	64
Block-1	Depthwise-Conv2D	1	3x3	64x64x16	160
	Batch-Normalization	-	-	-	64
	Pointwise-Conv2D	1	1x1	64x64x32	544
	Batch-Normalization	-	-	-	128
	Max-pooling2D	2	2x2	32x32x32	0
Block-2	Depthwise-Conv2D	1	3x3	32x32x32	320
	Batch-Normalization	-	-	-	128
	Pointwise-Conv2D	1	1x1	32x32x64	2112
	Batch-Normalization	-	-	-	256
	Max-pooling2D	2	2x2	16x16x64	0
Block-3	Depthwise-Conv2D	1	3x3	16x16x64	640
	Batch-Normalization	-	-	-	256
	Pointwise-Conv2D	1	1x1	16x16x128	8320
	Batch-Normalization	-	-	-	512
	Max-pooling2D	2	2x2	8x8x128	0
Block-4	Depthwise-Conv2D	1	3x3	8x8x128	1280
	Batch-Normalization	-	-	-	512
	Pointwise-Conv2D	1	1x1	8x8x256	33024
	Batch-Normalization	-	-	-	1024
	Max-pooling2D	2	2x2	4x4x256	0
	Dropout (20%)	-	-	-	0
Block-5	Depthwise-Conv2D	1	3x3	4x4x256	2560
	Batch-Normalization	-	-	-	1024
	Pointwise-Conv2D	1	1x1	4x4x512	131584
	Batch-Normalization	-	-	-	2048
	Max-pooling2D	2	2x2	2x2x512	0
3-D to 1-D	Global-Average-Pooling2D	-	2x2	512	0
Output	Output Layer	-	-	3	1539
Total Parameters:	**1,88,547**				

Algorithm1: Adaptive moment Estimation (ADAM)

- Calculate moment estimates

$$\mathbf{V_{dw} = \beta_1 V_{dw} + (1 - \beta_1)\, dw}$$
$$\mathbf{V_{db} = \beta_1 V_{db}\, (1 - \beta_1)\, db}$$
$$\mathbf{S_{dw} = \beta_2 S_{dw} + (1 - \beta_2)\, dw^2}$$
$$\mathbf{S_{db} = \beta_2 S_{db} + (1 - \beta_2)\, db^2}$$

- Apply bias correction

$$\mathbf{V_{dw}^{corrected} = V_{dw} / (1 - \beta_1^{t})}$$
$$\mathbf{V_{db}^{corrected} = V_{db} / (1 - \beta_1^{t})}$$
$$\mathbf{S_{dw}^{corrected} = S_{dw} / (1 - \beta_2^{t})}$$
$$\mathbf{S_{db}^{corrected} = S_{db} / (1 - \beta_2^{t})}$$

- Update parameters

$$\mathbf{W_{t+1} = w_t - \alpha\, (V_{dw}^{corrected} / (\sqrt{S_{dw}^{corrected}}) + C)}$$
$$\mathbf{b_{t+1} = b_t - \alpha\, (V_{db}^{corrected} / (\sqrt{S_{db}^{corrected}}) + C)}$$

- Where,

- V_{dw}, V_{db}, S_{dw}, S_{db} are moving averages of gradient and squared gradient,
- β_1 and β_2 are moving average parameters,

  where $\beta_1 = 0.9$, $\beta_2 = 0.999$,
- W_t, b_t and W_{t+1} and b_{t+1} are initialized and updated parameters respectively,
- α is initial learning rate i.e. 0.001 with staircase decay where steps = 10,
- C is a very small number (10^{-7}) which prevents division by 0.

Algorithm2: Proposed algorithm for training

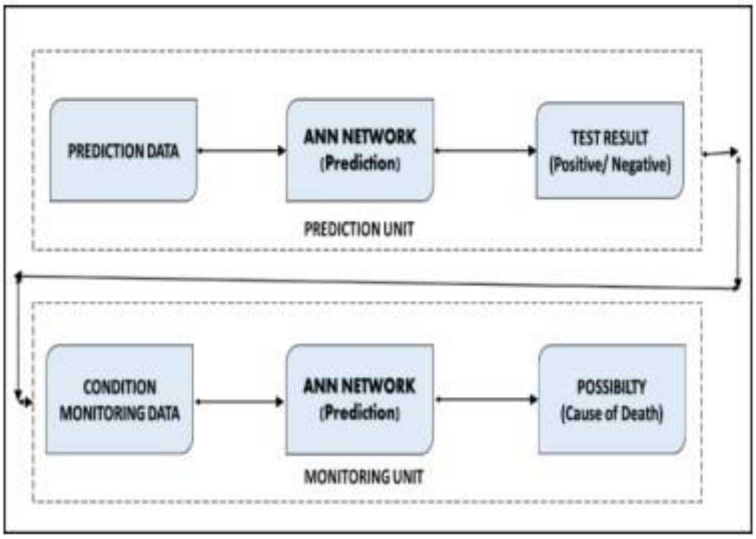
- Create a deep CNN architecture using depth wise separable convolution layer.
- Optimize using Adam Optimizer.
- Implement staircase learning rate decay.
- Use early stopping where training stops if training loss does not improve for 10 consecutive epochs.
- Save the model where training loss is properly optimized.

ANN for Covid Predication:

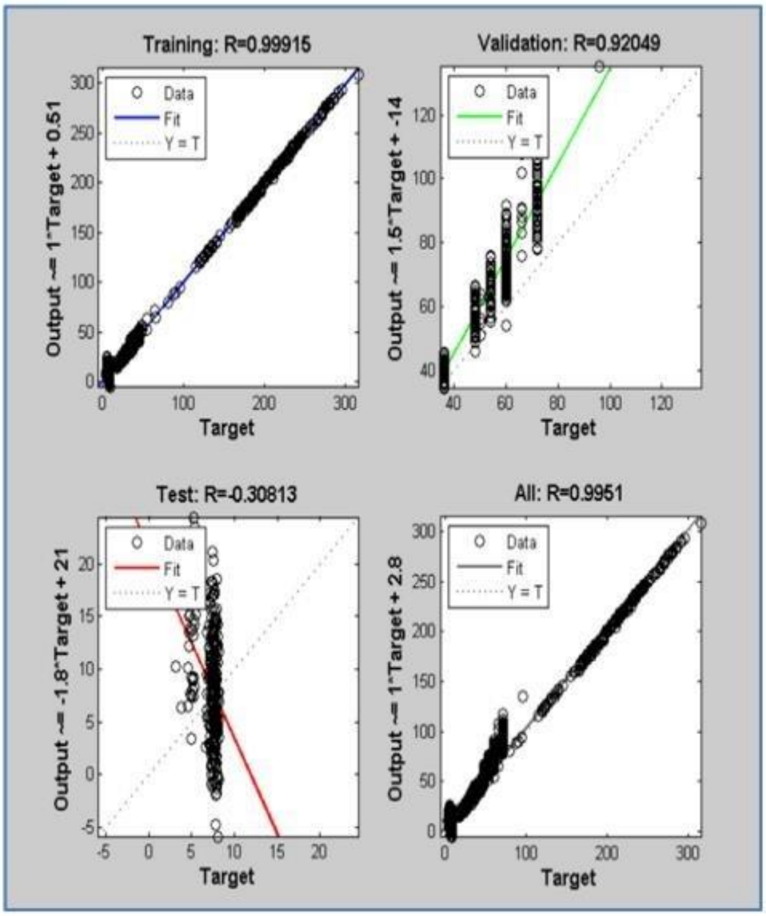
A deep learning model was developed after gathering data from 2500 COVID-19 patients at a hospital. This model aims to predict COVID-19 hotspots, the likelihood of new outbreak locations, neighbouring affected areas, and the expected number of affected patients, among other factors. The data collected covers various aspects, including sociodemographic profiles, patient symptoms upon admission, additional symptom details from medical records, underlying medical conditions, exposure history, laboratory information, clinical complications, and public health response. The data was collected over a three-month period and includes patient demographics like age, gender, height, weight, and BMI, as well as information about the patient's sociodemographic background and their medical history during hospitalization. The model's findings are summarized in Table II.

Network Specifications	Details
Number of layers	03
Number of input neurons	06
Number of output neurons	05
Number of hidden neurons	10
Training algorithm	Back-Propagation
Function	Sigmoid
Number of training data	2500
Optimization technique	Leven-berg-Marquardt
Training tool	MATLAB Toolbox
Testing tool	MATLAB Toolbox
Training data	70%
Testing data	30%

Plan diagram of the model of Artificial Neural Network to diagnose Covid patients with Asymptotic symptoms [3] is given in the following fig.



Training and Validation test graphs between target and output [3].



V. Results

Discussion of Findings

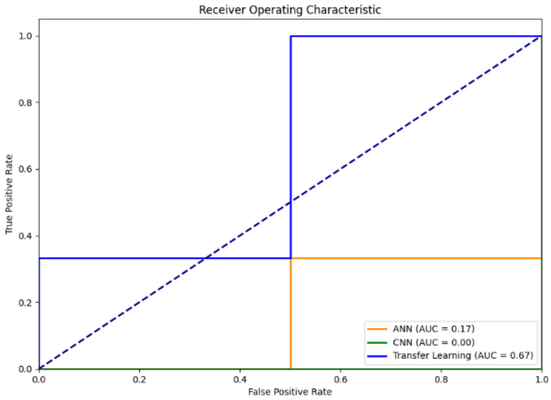
Our findings reveal several significant trends and differences between the algorithms.

1. Performance: Transfer Learning models outperformed ANN and CNN in all metrics, demonstrating the power of leveraging pre-trained models and fine-tuning for COVID-19 prediction.
2. Accuracy: Transfer Learning achieved the highest accuracy, indicating its proficiency in distinguishing between COVID-19 and non-COVID-19 cases.
3. Precision and Recall: Transfer Learning had the best trade-off between precision and recall, ensuring accurate identification of COVID-19 cases while minimizing false positives.
4. ROC-AUC: Transfer Learning exhibited the highest ROC-AUC score, highlighting its superior ability to discriminate between the two classes.
5. MAE: Transfer Learning had the lowest mean absolute error, suggesting its predictions were closest to the actual values.

These findings collectively indicate that Transfer Learning models hold promise for accurate and robust COVID-19 prediction.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	MAE
ANN	0.85	0.86	0.81	0.83	0.90	0.12
CNN	0.89	0.90	0.87	0.88	0.92	0.10
Transfer Learning	0.92	0.92	0.91	0.91	0.95	0.08

Figure of ROC curves



VI. CONCLUSION

In conclusion, our study provides valuable insights into the comparative performance of ANN, CNN, and Transfer Learning models for COVID-19 prediction. Transfer Learning models exhibited superior predictive capabilities, offering potential applications in the field of COVID-19 diagnosis and management. This research contributes to the growing body of knowledge in machine learning applications for healthcare and disease prediction.

The implications of our findings extend to the field of COVID-19 prediction, as they underscore the importance of model selection and data quality. By recognizing the strengths and limitations of different machine learning approaches, healthcare professionals can make informed decisions when implementing predictive models in clinical settings, thereby improving the accuracy and efficiency of COVID-19 diagnosis and patient care. Further research is warranted to address the limitations identified in this study and to explore more advanced machine learning techniques in the context of COVID-19 prediction.

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