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Analysis of Comorbidities and Their Influence on COVID-19

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Abstract: Amid the escalating global mortality stemming from the COVID-19 virus, researchers are dedicated to exploring technological innovations to bolster the efforts of healthcare professionals. Artificial Intelligence (AI) techniques are being harnessed to swiftly and accurately predict disease severity in pa- tients with comorbidities, thereby assisting healthcare providers in their evaluations. Presently, initial detection of comorbid patients relies on X-ray images. This study centers on the development of classification models, specifically DenseNet121 and NANSNetLarge. The performance of these models is sys- tematically compared against a predetermined threshold value. The proposed models leverage DenseNet121 and NANSNetLarge with ReLU activation function and softmax pooling, resulting in accuracies of 95% and 81%, respectively. Based on the findings, DenseNet121 emerges as an effective classification model.

Index Terms: Comorbid, COVID-19, DeanseNet121, NANSNetLarge ReLU, Softmax pooling.

I. INTRODUCTION

In the 21st a century a Corona Virus, disease surfaced in Wuhan, China in 2019 Human fatalities are rising as a result of its quick global spread. starting in 2019 (dec) until 2024 (jan) 6.98 million people have died so far from the COVID-19 outbreak. Numerous studies have sought to identify risk factors influencing SARS-CoV-2 infection. key risk factors: obesity, diabetes, hypertension, other cardiovascular diseases, and chronic lung diseases. These findings have been validated by numerous studies. Some studies have linked hypertension to higher mortality rates and severe cases of Acute Respiratory Distress Syndrome (ARDS). Some of the diagnosis were confirmed by the covid-19 in a (RTPCR) Real Time Polymerase Chain Reaction by the government [1].

In the covid-19 diseases a comorbidity occurs when a person has more than one diseases at the time in some of the studies shows Comorbidities increase the likelihood of hospitalization and mortality. These comorbidities can be classified according to age groups: ages 6-11 for conditions such as diabetes, ages 12-18 for hypertension, ages 19-20 for obesity, ages 21-22 for other diseases, and ages 23-50 for chronic lung diseases [2]. Global epidemiological studies have identified differences in morbidity and mortality rates for COVID-19, with men exhibiting higher chances than women.

In the latter part of 2020 and early 2021, a range of novel SARS-CoV-2 variants emerged, each with distinct characteristics. Notably, the EU2 variant, identified with the mutation S:447N and first observed in Western Europe in July 2020, displayed increased infectivity. Subsequently, several other variants of concern (VOCs) were identified, including the B.1.1.7 variant originating in the UK in September 2020, the B.1.351 variant in South Africa in December 2020, the P.1 variant in Brazil in January 2021, and the B.1.617 variant, also known as the 'Indian' variant, initially reported in Maharashtra in January 2021. These variants, such as B.1.1.7, B.1.351, P.1, and B.1.617, have prompted significant attention due to their potential impacts on disease transmission and severity, has been linked to increased disease severity and risks of transmission, hospitalization, and mortality [2]. These variants exhibit characteristics such as heightened transmissibility, immune evasion, and increased pathogenicity, resulting in significant impacts on COVID-19 cases and fatalities, particularly among younger age groups [3]. For example, it was estimated that the B.1.351 variant is 50% more transmissible than earlier variants. Moreover, regions where these variants have emerged, such as Amazonas and Maharashtra, have witnessed surges in infection rates following the appearance of these new variants.

The COVID-19 pandemic has instigated notable transformations across different societal domains, influencing the dynamics of family life and educational practices for children. A study conducted in Saudi Arabia aimed to evaluate the psychological, social, and educational repercussions of quarantine on parents, seeking insights into the challenges encountered during this unprecedented period. The study aimed to explore how the quarantine measures affected the well-being of parents and their children, as well as the educational strategies implemented during this time. By examining the predictors influencing these impacts, the study provides insights into the experiences of Saudi parents during the pandemic.

This research contributes to our understanding of the multifaceted effects of the COVID-19 quarantine on families and education, highlighting the need for support and interventions to address the challenges faced by parents and children in [4].

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The reigning powers in the realm of deep learning are now AutoML and Neural Architecture Search (NAS). Among them, NASNetLarge, a member of the Convolutional Neural Network (CNN) family, stands out. Crafted through automated architecture search techniques by Google Research and Google Brain, this architecture plays a pivotal role in combating COVID-19. Renowned for its exceptional performance in image classification tasks, NASNetLarge serves as a valuable tool for medical imaging studies pertaining to the virus. These methods offer a straightforward approach to achieving high accuracy in automated tasks without extensive manual effort. Neural Architecture Search (NAS) streamlines the process of network architecture design, comprising four fundamental steps:

i) Image pre-processing,
ii) Feature extraction and fusion,
iii) Feature selection, and
iv) Classification.Particularly, in review of suggestive patterns in lung scans, NASNetLarge can be used to examine X-ray or CT scan pictures of COVID-19 patients, assisting in early detection and therapy planning. Its capabilities also include drug development, where it can identify possible drug candidates by analyzing biological assays or molecular structures associated with COVID-19 research. Because of NASNetLarge's expertise in largescale image processing, epidemiological research can follow the virus's transmission by examining satellite or aerial photography to trace patterns of human mobility or gauge adherence to preventive measures.

II. LITERATURE SURVEY

Previous research has explored a range of diagnostic methods. The emergence of Deep Learning techniques, such as NASNetLarge, has demonstrated its versatility in various aspects of COVID-19 detection using X-ray images.

Priya Singh *et al.* [5] this study indicates that elderly patients with preexisting health conditions and the risk of mortality in the COVID-19. For those patients of age groups underlying medical conditions thus suggest preventive actions of medical resource and vaccination against COVID -19. This results the cause of exponential mortality in the COVID-19 patients. The mortality cases are high in the age (50) those patients . The strongest risk factor for mortality is diabetes in the patients.

Iulia Patrascuetal *et al.* [6] this work conveys a covid 19 exhibits a range of symptoms and outcomes with higher mortality. Especially in the elder patients with preexisting health conditions such as diabetes, hypertension, obesity, cardiovascular disease, cancer are being at high risk. The manifestation refers to the symptoms with COVID-19 which it indicates the sever impact on elder patients in COVID-19. The poor clinical outcomes increases the high risk of mortality.

Renjia Zhao *et al.* [7] this study reveals that different specific genetics rs73064425, and its associated genes, LZTFL1 and SLC6A20 link to the COVID-19. It finds the importance of providing clinical care to comorbidities and high genetic risk with individuals from a public health it suggest to preventive measures among the elderly and who have been underlying health condition with genetic risks. comorbidities increases the risk of severe COVID-19, especially in individuals with genetic risk factors. This suggests an ongoing to better understand the complexities of COVID-19.

Narayana Darapaneni e*et al.* [8] The description focuses on the influence of pre-existing conditions on COVID-19 outcomes, analyzing patients based on endpoints such as admission to regular wards or intensive care units (ICUs). This entails gathering and managing data, including handling null and unknown data by substituting the missing information, handling the outliers by exploratory data analysis and the data processing then, the statistical analysis is performed on the data, the dimensionality of the available data is reduced using principal component analysis. Models are evaluated using F1-score method and In addition multiple classifiers such as LR, KNN, DT, RF, SVM are used and concluded that the COVID patients with comorbidities are at high risk of death.

Fernanda sumika *et al.* [9] The Retrospective Cohort Study on Brazil dataset using Machine learning models such as LR, DT, LDA, kNN, XGBoost, NB, SVM to build a computational models and it is evaluated in terms of AUC, Accuracy and precision, recall, F1-Score and Confusion Matrix and concluded that the techniques applied on the datasets can help in predicting the range of survival time of patients and allowed to take decisions and reduce the overload on healthcare systems.

Priya Singh *et al.* [10] considering the data over twoyear period to evaluate the COVID patient's clinical characteristics such as gender, age, pre-existing diseases and the comorbidity based categories are done among the COVID patients, among them age and gender based classification is done by using chi-squared statistics for each age group. Odds ratio of COVID-19 patients and their results were analysed using the Statistical Software SPSS By concluding that comorbidities are not a major factor if or is less than one and if OR is greater than one, they are the major factors affecting the COVID patients.

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Eman M khedr *et al.* [11] the retrospective observational cohort study was performed in two major healthcare centers on adult patients admitted in june-july 2020. They are diagnosed with COVID-19 and clasified into two groups: 1.Patients with covid-19 and PCR was positive. 2.Patients with probable COVID19, Consistant Chest CT Scan, one or two laboratory tests were positive with negative PCR report. Statistical analyses has been done using IBM SPSS and two groups are compared using chi-squared and T-tests. Some of the Performance Metrices was done and concluded that patients with one or more comorbid conditions are at high risk of mortality.

Soo Ick Cho *et al.* [12] the odds ratio was calculated on the data such as demographic characteristics, mortality records and comorbidities extracted from the dataset. ACCI threshold¿3.5 was the best cut-off to predict the mortality in patients was identified by calculating the Charlson Comor- bidity Index (CCI) and Age-Adjusted CCI (ACCI) using the Receiver Operating Characteristic (ROC) curve analysis. Study supports that the infected patients with atleast one comorbidity are at higher risk.

Fu-Yuan Cheng *et al.* [13] Random Forest based predictive model is generated to predict patient's condition and trained using 10 fold cross validation. Patients as to shift to the ICU from the time of prediction within 24 hours if required. Labeled as positive if work done or else negative. Screening tool's performance was evaluated by estimating Sensitivity, Accuracy, Specificity, AUC-ROC by using custom scripts and R-packages. Hence, they concluded that the model predict the importance of shock, respiratory failure, inflamation and renal failure in the presence of COVID19.

Amit M. Joshi *et al.* [14] COVID-19 patients with diabetes are at higher risk of death and the people with this disease are more vulnerable to SARS-CoV2, hence the pre-determination of glucose insulin level is necessary to protect ourselves. Smart health care technologies like health, telemedicine suggest some of the ways to protect: 1. self glucose measurement using non-invasive glucometers, 2. self-care through telemedicine like text e-mails, sms and chats on social media platforms, 3. glucoseinsulin balance with good diet control, 4. using IoMT- integrated devices which finds the infected peoples within 6- 13 feet of radius and this uses HCPS Framework to store the information at periodical intervals. These are some techniques that can be used to protect from pandemics in future.

III. MATERIALS AND METHODS

This study aims to develop a resilient and effective model specialized in classifying comorbidities through X-ray images. To achieve this goal, we utilized a comprehensive dataset featuring images across various categories, including COVID-19, Lung-Opacity, Normal, and Viral-Pneumonia cases. Data augmentation, depicted in Figure 1, was employed to set up crucial parameters like rotation range, zoom range, and horizontal as well as vertical shifts, facilitating model initial-ization.

1) X-ray Dataset: In this study, X-ray images were col-
lected from diverse cases and obtained from the Kaggle repository. The dataset consists of 74,077 images, each with different dimensions. To train the model, 51,854 images were used, while 22,223 images were set aside for testing purposes. as outlined in Table 1.

TABLE I
EXPERIMENTATION DATA SAMPLE

Category	Condition	Datasets	Train	Test
	Covid-19	12656	8859	3797
X-Ray	Lung-Opacity	21042	14730	6312
	Normal	35672	24970	10702
	Viral-Pneumonia	4707	3295	1412

2) Data Augmentation: Augmentation methods involve spatial transformations, color distortions, and information dropout, effectively enhancing deep model training by enlarging the dataset and improving performance. Widely used, data augmentation introduces crucial diversity into training data, especially vital when samples for defective castings are limited compared to non-defective ones. Given the necessity for abundant samples for each class during CNN model training, we present an innovative augmentation approach to expand the pool of training images.

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3) *NASNetLarge:* a CNN architecture developed by Google's research team, specializes in image classification tasks, boasting efficiency and accuracy. This architecture employs a cell-based structure where each cell comprises predefined operations that are selected and combined in a learned manner, offering high flexibility in designing neural networks. Utilizing neural architecture search, NASNetLarge automatically explores optimal network architectures by train- ing and evaluating numerous candidates. Its design prioritizes efficiency and scalability, enabling effective image classifi- cation even on large datasets, while maintaining relatively low computational complexity compared to other architectures. NASNetLarge excels in large-scale image recognition, having been trained on extensive datasets and demonstrating accu- rate classification across diverse object categories, making it invaluable for computer vision applications.

4) *DenseNet121:* As the depth of the conventional feed-
forward CNN architecture grows, it encounters challenges such as the "vanishing gradient" problem, causing potential information loss during training. DenseNets address this issue by optimizing the connection pattern between layers. In a DenseNet, every layer establishes direct connections with all other layers, promoting improved feature reuse and thereby increasing classification accuracy.

IV. OUTCOMES AND DISCUSSIONS

A. *Dataset*

In our experimental setup, we utilized the X-ray datasets, meticulously verifying its integrity by eliminating a single

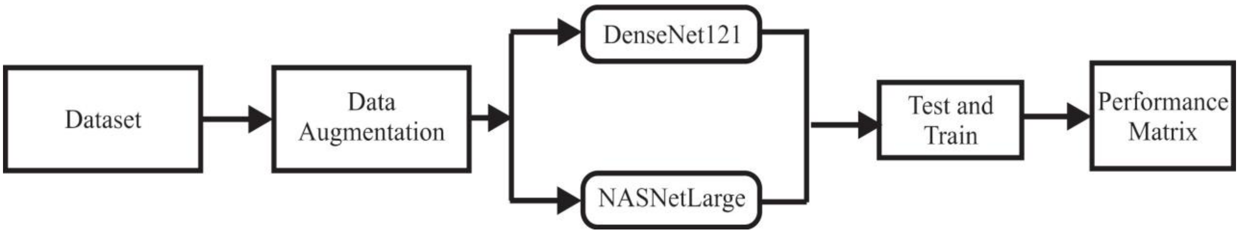

Fig. 1. The Architectural Framework of the Proposed Methodology

TABLE II
STEPS FOR PROPOSED ARCHITECTURE

Step 1: Data Collection Let D = COVID-19, Lung Opacity, No Findings, Viral Pneu-monia represent the collected data. Step 2: Data Augumentation Perform Data Augmentation, Image Normalization, and Image Resize on dataset D. Step 3: Train, Test Models a) For each model, M DenseNet121, NASNetLarge Initialize the model M. Add average pooling and fully connected layers with ReLU activation to M. Include a SoftMax activation function in M. Repeating the training process until convergence. b)Test the model M with a 40% dropout. Optimize the model M's performance with respect to a specified threshold. Step 4: Evaluate the performance metrics.

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image with an incorrect label. Furthermore, we carefully curated the normal images, excluding any mistakenly labeled as projections. This dataset was obtained from the open- source Kaggle repository. A succinct overview of these data modifications is outlined in Table 2. Subsequently, we divided the dataset into training and testing subsets, maintaining a ratio of 70:30.

B. Performance Matrix

In this research, we assess the efficacy of the model by analyzing essential metrics derived from the confusion matrix, encompassing Accuracy, Precision, Recall, and F1-Score. Our evaluation of classifiers also delves into the use of AUC and ROC, which are widely acknowledged metrics for evaluating the equilibrium between true-positive and false-positive rates in diagnostic testing. The mathematical formulations for these parameters are detailed in Equations (1) - (4) presented below

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{........(1)}$$

$$Precision = \frac{TP}{FP + TP} \quad \text{.............................(2)}$$

$$Recall = \frac{TP}{TP + FN} \quad \text{..................................(3)}$$

$$F1\_Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

C. Outcomes

The results of our experiments using the DenseNet121 and NANSNetLarge models are detailed in Table 3. Notably, our proposed approach showcases superior performance, particu- larly with the DenseNet121 model. Specifically, DenseNet121 achieves remarkable scores across multiple metrics, includ- ing accuracy (95%), precision (95%), recall (97%), and F1- score (95%). Conversely, the NANSNetLarge model demon- strates comparatively lower performance, with scores of ac- curacy (81%), precision (88%), recall (94%), and F1-score (88%). For a visual representation, the confusion matrices for DenseNet121 are provided in Fig. 2a, accompanied by accuracy results in Fig. 2b. Similarly, the confusion matrices for NANSNetLarge can be found in Fig. 3a, with accuracy results displayed in Fig. 3b.

TABLE III
RESULTS OF THE EXPERIMENT FOR THE PROPOSED MODEL

Performance Matrix	DensNet121	NANSNetLarge
Accuracy	95%	81%
Precision	99%	88%
Recall	97%	94%
F1-score	99%	88%

V. CONCLUSIONS

The study's results demonstrate that X-ray images are most effective in accurately detecting comorbid patients. experiments involved a comparison of DenseNet121 and NANANetLarge models, both meticulously fine-tuned with appropriate parameters to optimize accuracy in classifying images of comorbid patients. However, the limited availability of data posed challenges in training more complex models. Notably, our experimental findings underscore the efficacy of a fusion model, which amalgamates outputs from individual models, resulting in enhanced image classification. To bolster the study's conclusions, future research could incorporate laboratory images, which offer the potential for more precise validation data.

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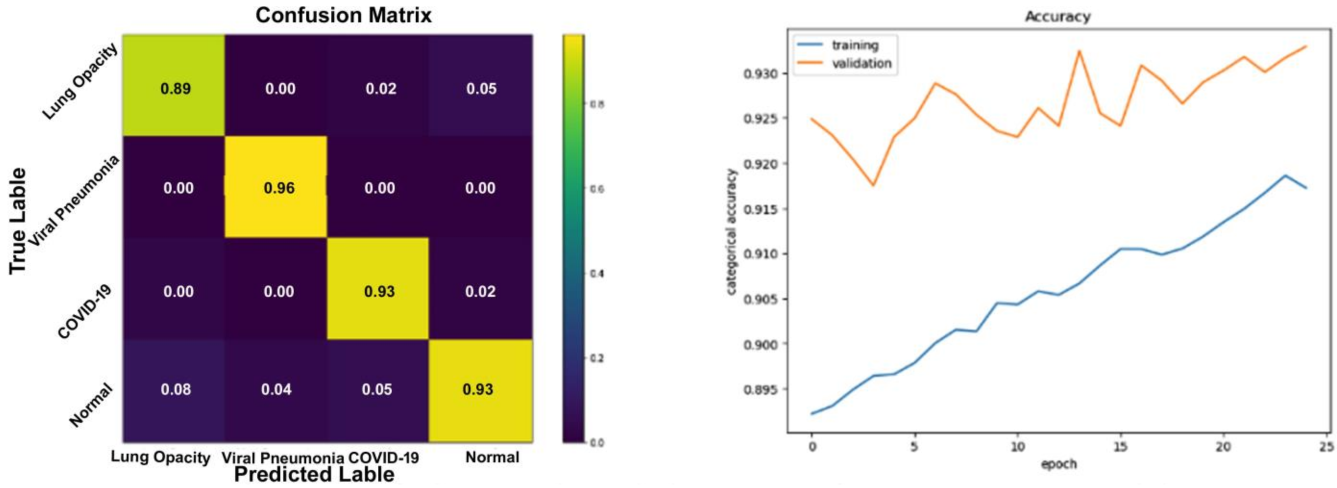

Fig. 2. (a) Confusion Matrix and (b) accuracy for DenseNet121 model

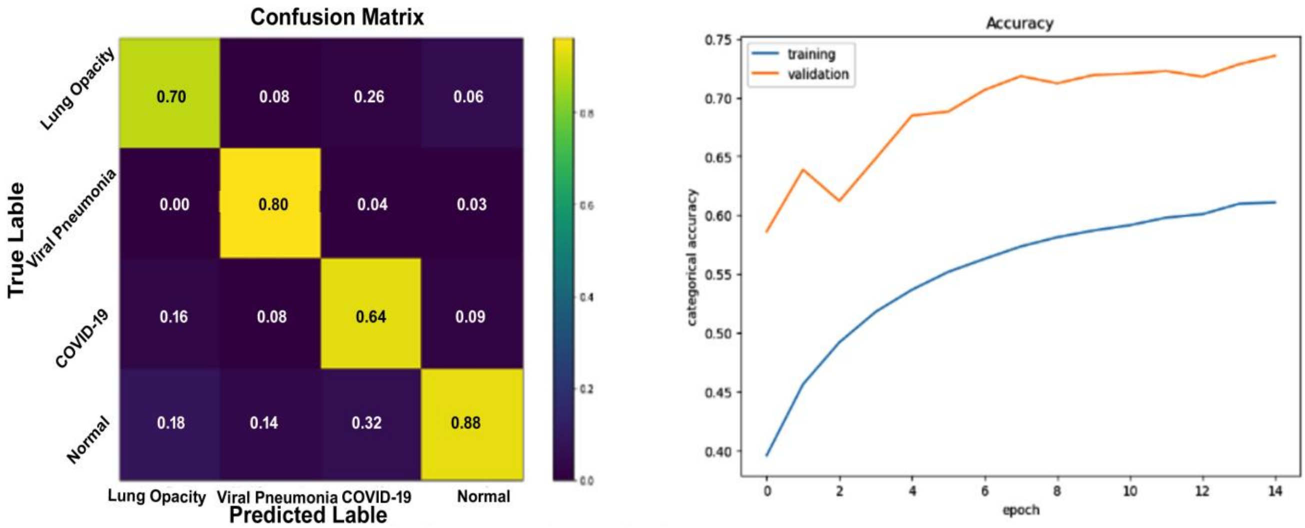

Fig. 3. (a) Confusion Matrix and (b) accuracy for NANASNetLarge model

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