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Research Article

Leveraging RegNetX002 for Automated Classification of COVID-19 and Other Lung Opacities in Chest X-ray Images

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ABSTRACT

The global corona virus epidemic has affected medical treatment. Because there are so many variations of newly developing infectious viruses, both the dangers they pose, and the effectiveness of vaccinations need much attention. To better comprehend this illness and investigate its transmission, individual diagnosis, and maybe other fascinating related concerns, it is helpful to learn more complex and interpretable models using COVID-19 data. On the other hand, the lack of accurately classified data is creating certain complications and challenges. Utilizing pre-trained Deep Neural Network (DNN) models on big datasets such as ImageNet has been done in earlier publications. This study evaluated the X002 version of the RegNet CNN architecture. Due to its less computationally costly design and very small number of parameters, the RegNet model is more computationally feasible for imaging applications compared to other CNN models. Self-regulation is a regulatory module that RegNet employs; it retrieves spatio-temporal data from the network's intermediate levels. Furthermore, RegNet's weight residual connections, batch normalization, and regularization mechanism approaches make it fast, scalable, and versatile. Our suggested approach successfully classified COVID-19, normal, pneumonia, and other lung opacities with an astounding accuracy of 95.37%, as determined after thorough testing and review.

Keywords: RegNetX002, COVID-19, Chest X-ray images, Deep learning, Classification, Pneumonia, Lung opacities, Medical image analysis, Diagnostic tool, Healthcare.

INTRODUCTION

Medical image classification has been a game-changer in the field of research, as it allows doctors to spend less time trying to diagnose diseases. The processing power is so great that we can get a lot done in a short amount of time. A variety of algorithms and models are continuously under development by researchers to improve the quality of results and to facilitate their work[1].

In a typical process for image classification, the two primary components are classification and labeling. All images must be classified and labeled as class A by the model for them to be regarded as class A. Researchers always strive for more effective and efficient algorithm outputs to make the procedure easier.

Training in supervised, semi-supervised, and unsupervised models is all possible using Deep Learning, a subset of Machine Learning[2]. Artificial Neural Networks served as an inspiration for this. Deep Learning can

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hierarchically take data and pull-out features, starting with low-level features and working its way up to high-level ones. One key distinction between deep learning and machine learning is the need for extensive dataset preprocessing before model training in machine learning[3]. Since deep learning models can handle noise and missing data with ease, there's no need to preprocess the data. Data preparation is not necessary at all.

Integrating health and medicine with comprehensive training is a fresh approach to promoting state-of-the-art methods. The research suggests that future deep learning studies should think about the technology's broad multi-dimensional application and how to successfully detect problems like COVID-19 or pandemic diagnosis. Skills in cross-useful areas, such as data retrieval, image processing, and protein structure prediction, must be hoarded. Combining it with state-of-the-art technology holds great promise for improving supervised learning methods for accurate Coronavirus detection. A new frontier in COVID-19 research has opened up because of deep learning. The fields of biology, epidemiology, machine vision, and basic semantic processing are all areas where deep learning has found use. Extending the reach of potential consequences, uncovering inconsistent data patterns, or deciphering common sense are all possible outcomes. The future has the potential for medicinal repurposing, protein structure prediction, and precise diagnostics.

According to Amyar et al.[4], convolutional neural networks (CNN) are an effective method for diagnosing chest radiograph abnormalities and other problems using deep learning. Using CNN, scientists analyze correct COVID-19 diagnoses during pandemic crises. Research by Zhang H. T. et al.[5] has shown that deep learning algorithms have the potential to improve the accuracy, precision, and timeliness of CT scan detection. When it comes to accurately diagnosing the COVID-19 virus, deep learning technology is a viable, useful, and appropriate method[6]. This finding highlights the possibility of using AI to improve image quality and identify the most cost-effective and reliable imaging techniques for the prevention of dangerous infections. To combat COVID-19, some researchers have now used deep learning. Research done in [7], [8], [9], [10] are among the notable contributions in the literature.

Radosavovic et al. [11] state that RegNetX002 is a convolutional neural network design. This model belongs to the RegNets family and is designed to provide a more efficient method for exploring neural network structures. This study seeks to enhance COVID-19 diagnostic instruments' accuracy and efficiency. These advancements may impact healthcare outcomes and public health policies.This study seeks to enhance COVID-19 diagnostic instruments' accuracy and efficiency. These advancements may impact healthcare outcomes and public health policies. faster and more accurately. The following goals will be pursued to accomplish this objective Building a trustworthy and precise technique with a tool for detecting COVID-19 instances from medical images is the goal of designing the classification and detection system. In regions without easy access to specialists or diagnostic tools, this method may help doctors diagnose and treat patients:

1. To amass and organize a database of medical images for COVID-19 case categorization. Several sources' chest X-rays and CT scans will be included in this collection, which will be labelled with COVID-19 presence/absence information.

2. To create and refine deep learning models that can use medical images to categorize COVID-19 patients. Models trained on the selected dataset will be based on cutting-edge deep learning architectures.

3. Assess the created models' efficacy in classifying COVID-19 instances from medical images. Accuracy, precision, loss, and f1-score are some of the common classification metrics that are used to assess the models.

Compare the models to other deep learning models and radiologist interpretation for COVID-19 diagnosis using medical images.

LITERATURE REVIEW

The classification of COVID-19 images has been tackled by several deep-learning algorithms. Inception V3, DenseNet, ResNet, and CNN are a few examples. To determine whether an image is positive or negative for COVID-19, these models use various architectures and methods[12], [13].

With almost 3,000 images in their dataset, Asif et al.[14] used the deep learning model Inception V3 to categorize the images. Their suggested model beat all the models mentioned in the research, showing promising results. Researchers Toraman et al.[15] examined the Capsnet model's accuracy for binary and multiclass classification using data collected using the model. Das et al.[16] conducted a literature study of several articles and used the architecture of the extreme Inception model in their research. A Deep Neural Network and a fuzzy inference engine formed the basis of the technique put out by Shaban et al.[17]. For better outcomes, they suggested a hybrid model. Ly[18] examined the Adaptive Nuero-Fuzzy Inference System (ANFIS) and compared its different components. The study effort of Sahlol et al.[19] made use of the various CNN models. In their comparison of CNN models with transfer learning, Apostolopoulos and Mpesiana[20] compared them to other top-tier deep learning models. The number of cases and fatalities were reported by Yadav [21], who also suggested an SVR-based model.

This work [22] uses a retrospective, single-center method at Wuhan's Jinyintan Hospital to study COVID-19 patients and their varied features. This research looked at epidemiological data from people who were exposed to viral epicenters, both for short and extended periods of time. Clinical findings, CT scans, lab data, and symptoms were all part of this investigation. Despite the study's lack of a clear emphasis on COVID-19 prediction, it did provide useful information on the disease's clinical consequences.

To aid in the identification of COVID-19 from chest X-rays, the authors of the study[23] explored the possibility of using deep learning (DL) algorithms in addition to conventional radiographic interpretation. According to Borkowski et al.[24], DL may be useful for several things, such as finding infections, making treatment priorities for patients, and speeding up diagnoses. Classifying and analyzing chest images using DL algorithms allows for the diagnosis of COVID-19 from medical images. CNN is used to extract features from images. Then, an ANN is trained to do detection and classification using these extracted characteristics. Using deep learning methods, the author's research [25] set out to identify visual alterations in CT scans of Chinese patients infected with COVID-19. The researchers showed that AI may be used for accurate COVID-19 prediction by developing a new diagnostic method that relies on identifying unique visual characteristics from CT images.

Using the in-built sensors of cell phones, the authors of research[26] presented a novel AI framework for the detection of COVID-19. With this system, data from several sensors can be harmoniously combined to predict the severity of pneumonia and the likelihood of contracting COVID-19. Symptoms of COVID-19 may be detected using the suggested framework by combining data from several sensors. Predicting the existence of COVID-19 relies heavily on the CT scan images that patients provide.

The research [27] suggests an alternate method of diagnosing COVID-19 that makes use of an automated detection system. The study presents three separate CNN-based models: ResNet50, InceptionV3, and Inception-ResNetV2. Through the analysis of chest X-ray radiographs, these models aim to detect instances of coronavirus pneumonia in patients. The suggested models have shown promising results in identifying cases of COVID-19 in patients. The authors have evaluated the three CNN models and compared their accuracy in classification performance. A beneficial and noninvasive diagnostic tool for properly detecting COVID-19 might be the newly created automated detection system, according to the study.

A novel method for patient mortality risk prediction based on three indicators was suggested in [28]. They built their prognostic prediction model on top of the XGBoost machine learning algorithm, which is well-known for its simple and effective way of assessing patients' risk of death. The study's authors shed light on the promise of machine learning algorithms for forecasting patient outcomes via their use of these algorithms; this has significant implications for clinical decision-making.

Multiple ML/DL algorithms and intensive care unit scoring systems were the subjects of a benchmarking evaluation in work[29]. Using freely available clinical datasets, these assessments included a range of clinical prediction tasks. Their study, however, is only focused on COVID-19 patient data.

The research in [30] presents the results of research that examined the use of CT scans for the diagnosis, monitoring, and follow-up of COVID-19. This research used CT scan data to classify COVID-19 symptoms as either "early," "advanced," "critical," or "complicated" according to the size and severity of the lesions. We can learn more about the severity and course of diseases using this categorization. Possible aid in monitoring COVID-19 development and early detection of pulmonary problems might be provided by an AI-enabled chest imaging system.

All of the articles above have stressed the need for AI and machine learning to deal with COVID-19 in its many forms, from detection and prediction to monitoring. Results from these investigations on COVID-19 diagnosis using medical imaging (e.g., chest X-rays and CT scans) and patient mortality risk assessment have been encouraging. It is important to note, however, that these studies do have their limitations. A common flaw in these studies is that they either used data from a particular hospital or country, or they relied on very tiny samples. The results may not apply to larger groups if these limitations are present. Furthermore, there has been a lack of validation of some machine learning models on separate datasets and inconsistent data quality in these investigations.

Several recent research have shown that deep learning models might be useful for diagnosing COVID-19, but a lot of work remains before these models can be employed in clinical practice.

MATERIALS AND METHODS

I. DataSet

The Health Imaging Data Bank of the Valencian Region (BIMCV)[31] provided the dataset used in this study. In all, there are 21,165 X-ray images included. Ten,192, 6012, 3616, and 1,345 X-ray images of healthy, opacified, diseased, and viral pneumoniaed lungs are included in the collection.

II. Methodology

This study used the RegNetX architecture, which is well-suited for training deep neural networks on massive datasets due to its efficiency and scalability. To achieve efficient feature extraction, RegNetX has a modular architecture with recurring stages of bottleneck blocks.

1. Mathematical Formulation:

- Let X={x1,x2,...,xN} represent the set of chest X-ray images in the dataset, where each xi is a grayscale image.
- Corresponding labels are denoted by Y={y1,y2,...,yN}, where each yi represents the class label (COVID-19, normal, pneumonia, other lung opacities) associated with the respective image xi.
- The RegNetX model can be represented as fθ:X→Y, where θ represents the parameters of the deep neural network.

The classification task aims to learn the optimal parameters θ∗ that minimize the classification error. This can be formulated as:

$$\theta^* = \arg\min_\theta \frac{1}{N}\sum_{i=1}^{N} \mathcal{L}(f_\theta(x_i), y_i) (1)$$

where $\mathcal{L}$ denotes the chosen loss function, such as cross-entropy loss.

A prominent network search tool in the last several years is Neural Architecture Search (NAS)[32]. NAS uses neural structure search technology to determine the optimal collection of parameters (compound coefficients), and hence the best model, however it is computationally expensive and demands a lot of resources. A typical NAS approach uses instances of individual networks, which implies only one network at a time. This approach has limitations such as a lack of generalizability and many ways to change the parameters. Thus, the academics shifted their focus to estimating the total network design space, which entails gauging the interrelationships of several factors including the breadth and depth of the network design in connection to the network objective. In the RegNetX approach, NAS technology is used. Figure 1 depicts the general layout of the RegNet network.

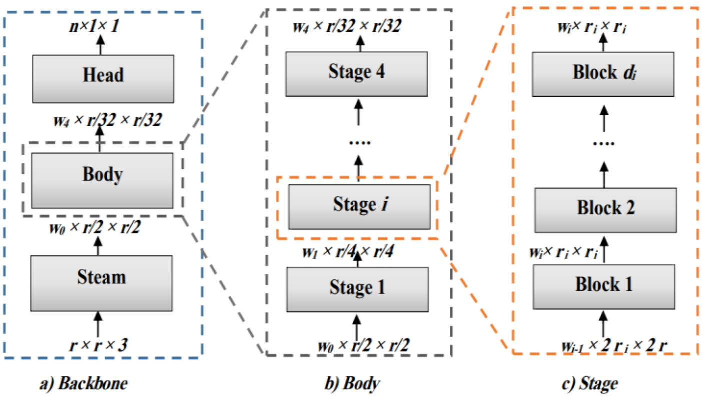

Figure1: Backbone, body, and stage of RegNetX model

The three main components of the RegNetX backbone network are the stem, the body, and the head. The model's simplicity in the steam and head networks allows it to concentrate on the body network. The following attributes make up the stem: a convolution layer with 32 convolution cores, a convolution kernel size of 3 × 3, an activation function called ReLU, a step length of 2, and default Batch Normalization (BN). The body structure consists of four phases and is stacked. After each step, the input matrix's width and height were cut in half from their original dimensions. To build each level, a sequence of block stacks is assembled. Group and conventional convolutions both have two steps in the first block and one step in each subsequent block. Lastly, the classification network's head consists of two layers: fully connected and global average pooling. This is how the RegNet X002 variation is described:

a. Basic Block:

Operations such as convolution, batch normalization, activation function (e.g., ReLU), and down sampling (if needed) are the fundamental building blocks of RegNetX. Here is the mathematical representation of a fundamental block:

$$BasicBlock(x)=ReLU(BatchNorm(Conv(x)))$$

where:

- x represents the input feature map.
- Conv(·) denotes the convolution operation.
- BatchNorm(·) denotes batch normalization.
- ReLU(·) represents the Rectified Linear Unit activation function.

b. Stage:

Multiple basic blocks are organized in a series to form a stage in RegNetX. The feature maps' channel counts are normally increased with each step, enabling more intricate feature extraction. The following is the mathematical representation of a stage:

$$Stage(x)=BasicBlock_N(BasicBlock_{N-1}(\ldots(BasicBlock_1(x))\ldots))$$

where:

- N represents the number of basic blocks in the stage.
- $BasicBlock_i(\cdot)$ represents the i^{th} basic block in the stage.

c. RegNetX Architecture**:**

Several stages are organized in a sequential fashion in the RegNetX design. At each level, the feature maps' spatial dimensions are reduced, and the number of channels grows, allowing for hierarchical feature extraction. From a mathematical perspective, the RegNetX architecture looks like:

$$RegNetX(x)=StageM(Stage_{M-1}(\ldots(Stage1(x))\ldots))$$

where:

M represents the number of stages in the RegNetX architecture.

$Stage_i(\cdot)$ represents the i^{th} stage in the architecture.

4. Mathematical Formulation:

Given an input feature map x, the output of the RegNetX architecture can be computed as follows:

$RegNetX(x)=Stage_M(Stage_{M-1}(\ldots(Stage_1(x))\ldots))$

The RegNetX architectural parameters (θ) comprise convolutional layer weights, biases, and batch normalization layer parameters.

d. Training:

Using methods based on backpropagation and gradient descent, the RegNetX architecture's parameters θ are optimized during the training phase. The goal is to reduce the value of a predetermined loss function $\mathcal{L}$, which is usually used to quantify the difference between the expected results and the actual labels on the ground

$$\theta^* = \arg\min_\theta \frac{1}{N}\sum_{i=1}^{N}\mathcal{L}(\mathrm{RegNetX}(x_i), y_i) \quad (2)$$

where:

- x_i represents the i^{th} input feature map.
- y^i represents the corresponding ground truth label.
- N is the total number of training samples.

III. Model Training

Training Procedure: Supervised learning is used to train the model, with back propagation and gradient descent-based approaches used to optimize the RegNetX architecture's parameters.

Optimization Algorithm: During training, the model's parameters are updated effectively using the Adam optimizer[33].

Hyper parameters Tuning: The model's performance is fine-tuned by utilizing grid search or random search to adjust hyper parameters like learning rate, batch size, and regularization approaches.

IV. Evaluation Metric

Common assessment measures including accuracy, precision, recall, F1-score, and confusion matrix are used to assess the trained model's performance.

The complete pseudocode for the research methodology is as follows:

Pseudocode
1. Preprocessing: *- Read chest X-ray images* *- Apply preprocessing techniques (e.g., resizing, normalization) to enhance image quality* *2. Training the RegNetX002 model:* *- Initialize RegNetX002 architecture with pre-trained weights* *- Freeze initial layers (if necessary) to prevent overfitting on small datasets* *- Define loss function (e.g., cross-entropy loss) and optimizer (e.g., Adam)* *- Split dataset into training and validation sets* *- Train the model using training images:* *for each epoch do:* *for each batch of images do:* *Forward pass: Obtain predictions using the model*

Calculate loss

$$\mathcal{L}(y,\hat{y}) = \frac{1}{N}\sum_{i=1}^{N}[y_i\, log(\hat{y}_i) + (1-y_i)log(1-\hat{y}_i)] \quad (3)$$

where y represents the ground truth labels, ŷ represents the predicted probabilities, and N is the number of samples.

Backward pass: Update model weights using gradient descent

$$w_{new} = w_{old} - \alpha\frac{\partial\mathcal{L}}{\partial\, w_{old}} \quad (4)$$

where w_{old} *and* w_{new} *represent the old and updated weights, respectively, and α is the learning rate.*

- Evaluate model performance on validation set to monitor overfitting

3. Fine-tuning:

- Fine-tune the pre trained RegNetX002 model on the dataset specific to COVID-19, normal, pneumonia, and other lung opacities:

for each epoch do:

for each batch of images do:

Forward pass: Obtain predictions using the model

Calculate loss

Backward pass: Update model weights using gradient descent

- Monitor validation performance to avoid overfitting

4. Classification:

- Use the trained RegNetX002 model to classify chest X-ray images:

for each image in the test set do:

Forward pass: Obtain predictions using the model

Choose the class with the highest predicted probability

RESULT AND DISCUSSION

The proposed model was implemented with AMD Ryzen 7(Clock speed 2.5 GHz) and NVIDIA GeForce GTX with CUDA Support required for GPU acceleration. Python 3.11.4 with the following libraries was used.

- TensorFlow: Deep learning framework for building and training neural networks.
- NumPy: For numerical computing and array operations.
- Matplotlib or Seaborn: For data visualization and plotting.
- Scikit-learn: For evaluation metrics and data preprocessing tasks.
- Pandas: For data manipulation and analysis.
- OpenCV: For image preprocessing and augmentation.

The model's weights and biases may be modified during training to enhance task performance. The non-trainable parameters are not updated during training.

RegNetX002 architecture has a total of 2,432,132 parameters, with 2,411,284 trainable parameters and 20,848 non-trainable parameters(As shown in figure 2).

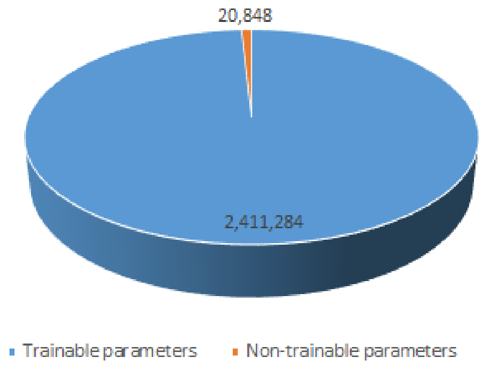

Figure2: Trainable parameters non-trainable parameters

Figure 3 shows the close alignment between the training, validation, and test accuracies. It suggests that the model is well-trained, has good generalization capabilities, and is not overfitting to the training data.

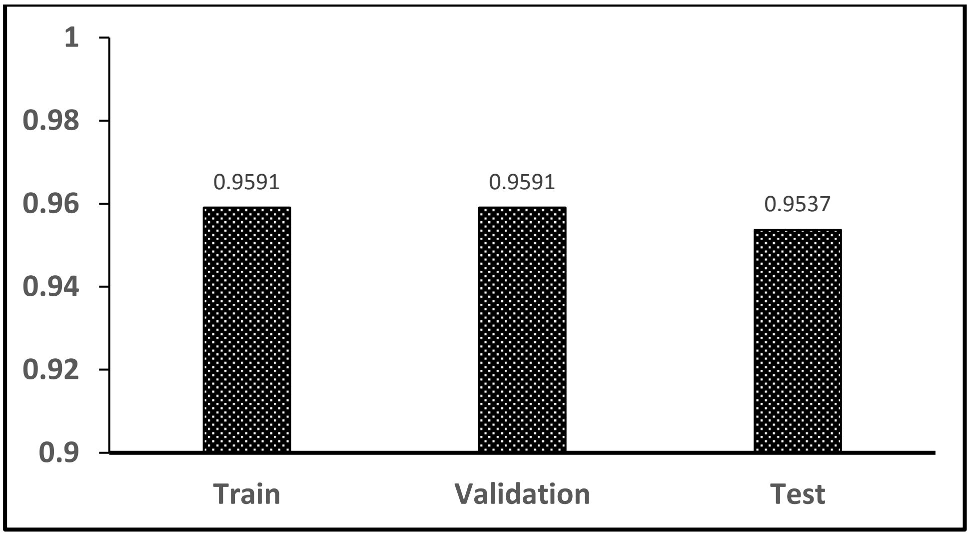

Figure3: Accuracy comparison of the proposed model

In Figure 4, a train loss value of 0.1257 suggests the model is performing reasonably well on the training data. Validation loss of 0.1176 is somewhat lower than the train loss, which is excellent. It shows that the model is not overfitting to training data and generalizing effectively to validation data.

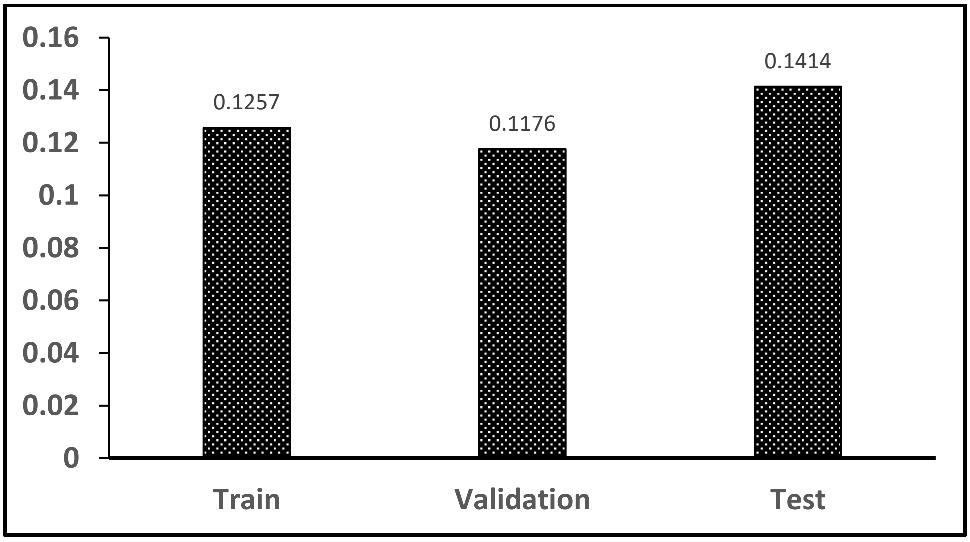

Figure4: Loss comparison of the proposed model

Figures 5 and 6 illustrate the loss and accuracy of validation with respect to epoch-wise training.

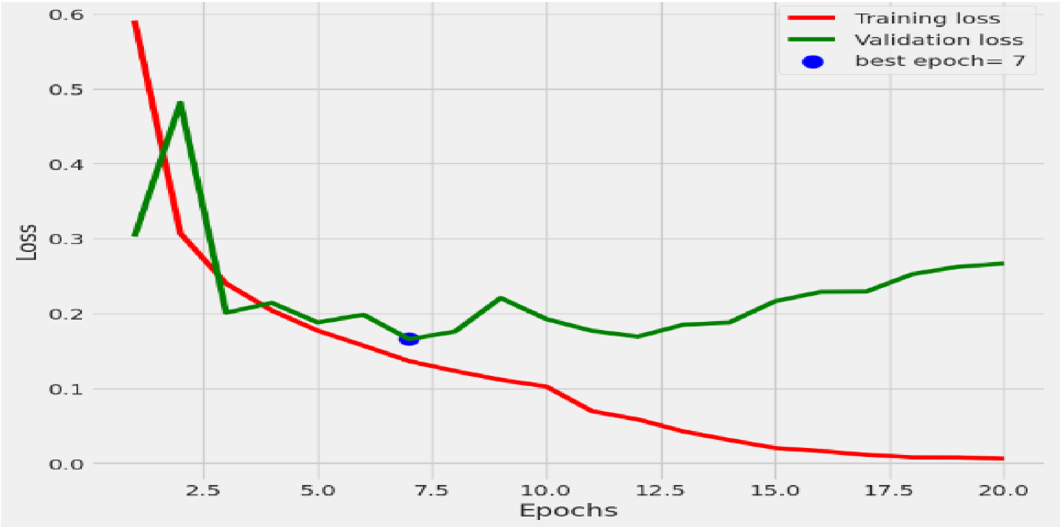

Figure5: Epoch-wise Training and validation loss

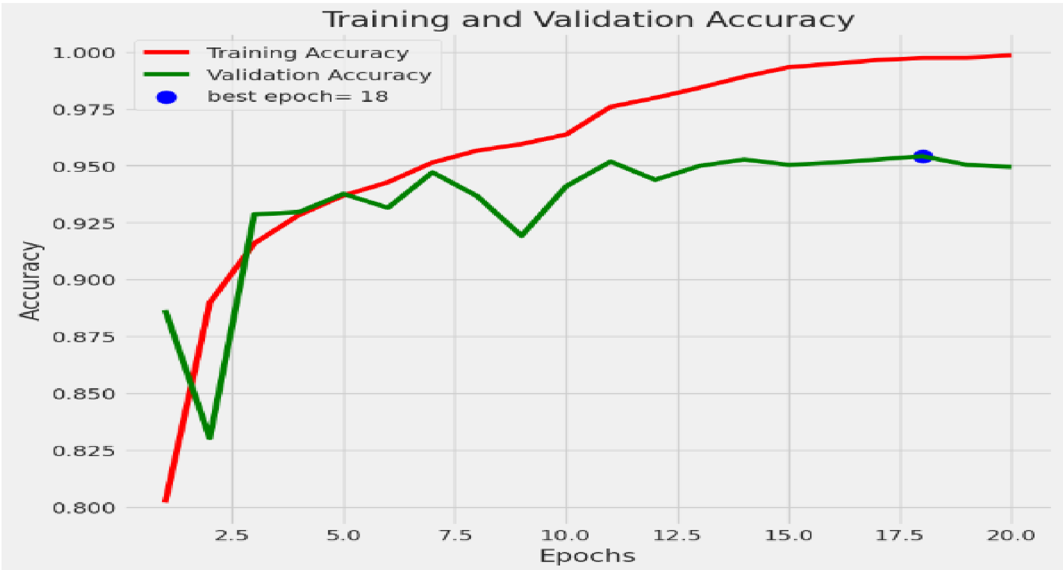

Figure6: Epoch-wise Training and validation accuracy

Figure 7 shows the aligned high values of 0.96 (96%) across precision, recall, and F1-score that indicate that the RegNetX002 architecture is a highly effective model for the task it was designed for. This level of performance is generally considered excellent, as it demonstrates the model's ability to:

- Accurately identify positive instances (high precision)
- Capture the majority of positive instances (high recall)
- Maintain a well-balanced trade-off between precision and recall (high F1 score)

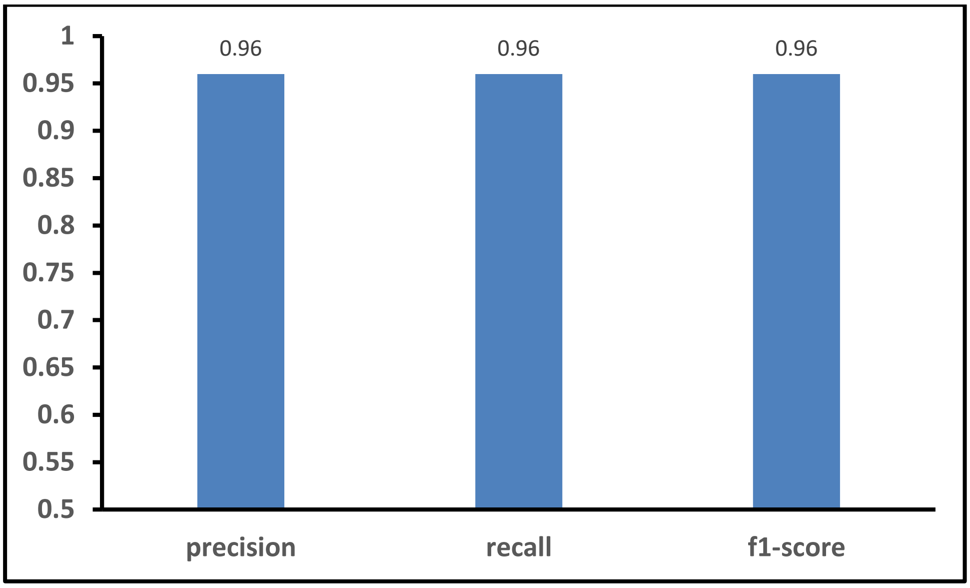

Figure7: Performance of the proposed model

From the confusion matrix shown in Figure 8, we can infer the following:

- The model is performing very well in classifying COVID-19, Lung opacity, and Viral pneumonia, with high true positive rates for each class.
- There are some false positives and false negatives, but the overall performance seems quite good.
- The model may have some difficulty distinguishing between the two "Lung opacity" classes, as there are some misclassifications between them.

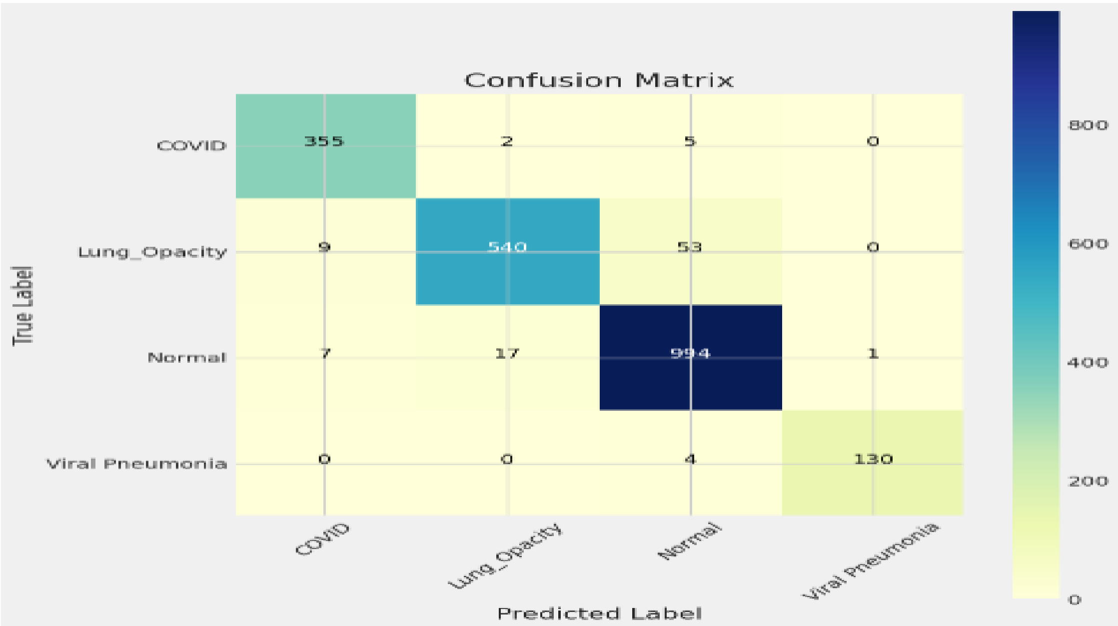

Figure8: Confusion Matrix

The proposed model was compared with EfficientNetB0[34], NASNetMobile[35], and ResNetRS50[36]. Comparison results in terms of test accuracy and loss are shown in Table 1.

Table 1: Performance Table

Models	Test Accuracy	Test Loss
EfficientNetB0	0.9211	0.3578
NASNetMobile	0.9523	0.1678
RegNetX002 architecture	0.9537	0.1414
ResNetRS50	0.9419	0.1759

Since the RegNetX002 design shows the best combination of test accuracy and loss, it can be inferred from the comparison findings that it is the best model for the job at hand. This indicates that the RegNetX002 architecture achieves the best results in terms of accuracy and loss value on the test dataset..

CONCLUSION

Recently, medical imaging has been suggested for COVID-19 diagnosis. CT scans and chest X-rays may detect consolidation and ground-glass opacities in COVID-19 pneumonia. Deep learning models may solve medical picture interpretation problems. This study shows how well RegNetX002 can recognize lung opacity in chest X-ray images of COVID-19, normal, pneumonia, and others. In comparison to other top-tier designs like EfficientNetB0, NASNetMobile, and ResNetRS50, the RegNetX002 model scored an exceptional test accuracy of 95.37%. This remarkable precision exemplifies the model's remarkable capacity to discriminate among several lung diseases, particularly the crucial differentiation between COVID-19 and other respiratory ailments.

The proposed deep learning models can be improved for COVID-19 diagnosis in the future in several ways. Model resilience and adaptability to varied image situations may be enhanced with the use of techniques like CutMix, which supplement training data. There is hope for improved accuracy by investigating and optimizing a larger pool of pre-trained models for COVID-19 identification. While there are still obstacles to overcome in data fusion, integrating data from several medical imaging types might provide a more complete image of patients' ailments. When it comes to identifying COVID-19, the interpretability of deep-learning models used for medical image analysis is very crucial. It is critical to find ways to make these models' decision-making process more clear so that their outputs can be understood and trusted. Medical practitioners will have faith in and be able to make good use of these models in the clinic because of their interpretability.

REFERENCES

[1] S. Bhardwaj, S. Jain, N. K. Trivedi, A. Kumar, and R. G. Tiwari, "Intelligent Heart Disease Prediction System Using Data Mining Modeling Techniques," pp. 881–891, 2022, doi: 10.1007/978-981-19-0707-4_79.

[2] N. K. Trivedi, R. G. Tiwari, A. Anand, V. Gautam, D. Witarsyah, and A. Misra, "Application of Machine Learning for Diagnosis of Liver Cancer," *Proceedings - International Conference Advancement in Data Science, E-Learning and Information Systems, ICADEIS 2022*, 2022, doi: 10.1109/ICADEIS56544.2022.10037379.

[3] N. K. Trivedi, R. G. Tiwari, A. K. Agarwal, and V. Gautam, "A Detailed Investigation and Analysis of Using Machine Learning Techniques for Thyroid Diagnosis," *2023 International Conference on Emerging Smart Computing and Informatics, ESCI 2023*, 2023, doi: 10.1109/ESCI56872.2023.10099542.

[4] A. Amyar, R. Modzelewski, H. Li, and S. Ruan, "Multi-task deep learning based CT imaging analysis for COVID-19 pneumonia: Classification and segmentation," *Comput Biol Med*, vol. 126, p. 104037, Nov. 2020, doi: 10.1016/J.COMPBIOMED.2020.104037.

[5] H. tao Zhang *et al.*, "Automated detection and quantification of COVID-19 pneumonia: CT imaging analysis by a deep learning-based software," *Eur J Nucl Med Mol Imaging*, vol. 47, no. 11, pp. 2525–2532, Oct. 2020, doi: 10.1007/S00259-020-04953-1/TABLES/4.

[6] S. D. Thepade and K. Jadhav, "Covid19 identification from chest x-ray images using local binary patterns with assorted machine learning classifiers," *2020 IEEE Bombay Section Signature Conference, IBSSC 2020*, pp. 46–51, Dec. 2020, doi: 10.1109/IBSSC51096.2020.9332158.

[7] A. Waheed, M. Goyal, D. Gupta, A. Khanna, F. Al-Turjman, and P. R. Pinheiro, "CovidGAN: Data

Augmentation Using Auxiliary Classifier GAN for Improved Covid-19 Detection," *IEEE Access*, vol. 8, pp. 91916–91923, 2020, doi: 10.1109/ACCESS.2020.2994762.

[8] A. S. Al-Waisy *et al.*, "COVID-CheXNet: hybrid deep learning framework for identifying COVID-19 virus in chest X-rays images," *Soft comput*, vol. 27, no. 5, pp. 2657–2672, Mar. 2023, doi: 10.1007/S00500-020-05424-3/TABLES/8.

[9] L. Wang, Z. Q. Lin, and A. Wong, "COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images," *Scientific Reports 2020 10:1*, vol. 10, no. 1, pp. 1–12, Nov. 2020, doi: 10.1038/s41598-020-76550-z.

[10] J. D. Arias-Londono, J. A. Gomez-Garcia, L. Moro-Velazquez, and J. I. Godino-Llorente, "Artificial Intelligence Applied to Chest X-Ray Images for the Automatic Detection of COVID-19. A Thoughtful Evaluation Approach," *IEEE Access*, vol. 8, pp. 226811–226827, 2020, doi: 10.1109/ACCESS.2020.3044858.

[11] I. Radosavovic, R. P. Kosaraju, R. Girshick, K. He, and P. Dollár, "Designing network design spaces," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 10425–10433, 2020, doi: 10.1109/CVPR42600.2020.01044.

[12] K. Sahinbas and F. O. Catak, "Transfer learning-based convolutional neural network for COVID-19 detection with X-ray images," *Data Science for COVID-19 Volume 1: Computational Perspectives*, pp. 451–466, Jan. 2021, doi: 10.1016/B978-0-12-824536-1.00003-4.

[13] F. A. Breve, "COVID-19 detection on Chest X-ray images: A comparison of CNN architectures and ensembles," *Expert Syst Appl*, vol. 204, p. 117549, Oct. 2022, doi: 10.1016/J.ESWA.2022.117549.

[14] S. Asif, Y. Wenhui, H. Jin, Y. Tao, and S. Jinhai, "Classification of COVID-19 from Chest X-ray images using Deep Convolutional Neural Networks," *medRxiv*, p. 2020.05.01.20088211, Jun. 2020, doi: 10.1101/2020.05.01.20088211.

[15] S. Toraman, T. B. Alakus, and I. Turkoglu, "Convolutional capsnet: A novel artificial neural network approach to detect COVID-19 disease from X-ray images using capsule networks," *Chaos Solitons Fractals*, vol. 140, p. 110122, Nov. 2020, doi: 10.1016/J.CHAOS.2020.110122.

[16] N. Narayan Das, N. Kumar, M. Kaur, V. Kumar, and D. Singh, "Automated Deep Transfer Learning-Based Approach for Detection of COVID-19 Infection in Chest X-rays," *IRBM*, vol. 43, no. 2, pp. 114–119, Apr. 2022, doi: 10.1016/J.IRBM.2020.07.001.

[17] W. M. Shaban, A. H. Rabie, A. I. Saleh, and M. A. Abo-Elsoud, "Detecting COVID-19 patients based on fuzzy inference engine and Deep Neural Network," *Appl Soft Comput*, vol. 99, p. 106906, Feb. 2021, doi: 10.1016/J.ASOC.2020.106906.

[18] K. T. Ly, "A COVID-19 forecasting system using adaptive neuro-fuzzy inference," *Financ Res Lett*, vol. 41, p. 101844, Jul. 2021, doi: 10.1016/J.FRL.2020.101844.

[19] A. T. Sahlol, D. Yousri, A. A. Ewees, M. A. A. Al-qaness, R. Damasevicius, and M. A. Elaziz, "COVID-19 image classification using deep features and fractional-order marine predators algorithm," *Scientific Reports 2020 10:1*, vol. 10, no. 1, pp. 1–15, Sep. 2020, doi: 10.1038/s41598-020-71294-2.

[20] I. D. Apostolopoulos and T. A. Mpesiana, "Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks," *Phys Eng Sci Med*, vol. 43, no. 2, pp. 635–640, Jun. 2020, doi: 10.1007/S13246-020-00865-4/TABLES/6.

[21] M. Yadav, M. Perumal, and M. Srinivas, "Analysis on novel coronavirus (COVID-19) using machine learning methods," *Chaos Solitons Fractals*, vol. 139, p. 110050, Oct. 2020, doi: 10.1016/J.CHAOS.2020.110050.

[22] D. Wang *et al.*, "Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China," *JAMA*, vol. 323, no. 11, pp. 1061–1069, Mar. 2020, doi: 10.1001/JAMA.2020.1585.

[23] N. Chen *et al.*, "Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study," *The Lancet*, vol. 395, no. 10223, pp. 507–513, Feb. 2020, doi: 10.1016/S0140-6736(20)30211-7.

[24] A. A. Borkowski, N. A. Viswanadhan, L. B. Thomas, R. D. Guzman, L. A. Deland, and S. M. Mastorides, "Using Artificial Intelligence for COVID-19 Chest X-ray Diagnosis," *Federal Practitioner*, vol. 37, no. 9, p. 398, Sep. 2020, doi: 10.12788/FP.0045.

[25] S. Wang *et al.*, "A deep learning algorithm using CT images to screen for Corona virus disease (COVID-19)," *Eur Radiol*, vol. 31, no. 8, pp. 6096–6104, Aug. 2021, doi: 10.1007/S00330-021-07715-1/FIGURES/5.

[26] H. S. Maghded, K. Z. Ghafoor, A. S. Sadiq, K. Curran, D. B. Rawat, and K. Rabie, "A Novel AI-enabled Framework to Diagnose Coronavirus COVID-19 using Smartphone Embedded Sensors: Design Study," *Proceedings - 2020 IEEE 21st International Conference on Information Reuse and Integration for Data Science, IRI 2020*, pp. 180–187, Aug. 2020, doi: 10.1109/IRI49571.2020.00033.

[27] A. Narin, C. Kaya, and Z. Pamuk, "Automatic Detection of Coronavirus Disease (COVID-19) Using X-ray Images and Deep Convolutional Neural Networks," *Pattern Analysis and Applications 2021 24:3*, vol. 24, no. 3, pp. 1207–1220, Mar. 2020, doi: 10.1007/s10044-021-00984-y.

[28] L. Yan *et al.*, "A machine learning-based model for survival prediction in patients with severe COVID-19 infection," *medRxiv*, p. 2020.02.27.20028027, Mar. 2020, doi: 10.1101/2020.02.27.20028027.

[29] S. Purushotham, C. Meng, Z. Che, and Y. Liu, "Benchmarking deep learning models on large healthcare datasets," *J Biomed Inform*, vol. 83, pp. 112–134, Jul. 2018, doi: 10.1016/J.JBI.2018.04.007.

[30] Z. Z. Jiang *et al.*, "The Role of Imaging Techniques in Management of COVID-19 in China: From Diagnosis to Monitoring and Follow-Up," *Med Sci Monit*, vol. 26, pp. e924582-1, 2020, doi: 10.12659/MSM.924582.

[31] "BIMCV-COVID19 – BIMCV." Accessed: Mar. 12, 2024. [Online]. Available: https://bimcv.cipf.es/bimcv-projects/bimcv-covid19/#1590859488150-148be708-c3f3

[32] Y. Liu, Y. Sun, B. Xue, M. Zhang, G. G. Yen, and K. C. Tan, "A Survey on Evolutionary Neural Architecture Search," *IEEE Trans Neural Netw Learn Syst*, vol. 34, no. 2, pp. 550–570, Feb. 2023, doi: 10.1109/TNNLS.2021.3100554.

[33] R. G. Tiwari, A. Misra, and N. Ujjwal, "Comparative Classification Performance Evaluation of Various Deep Learning Techniques for Sentiment Analysis," pp. 304–309, Jan. 2023, doi: 10.1109/ICSC56524.2022.10009471.

[34] T. Kivrak *et al.*, "EfDenseNet: Automated Pulmonary Hypertension Detection Model Based on EfficientNetb0 and DenseNet201 Using CT Images," *IEEE Access*, vol. 11, pp. 142711–142724, 2023, doi: 10.1109/ACCESS.2023.3338228.

[35] I. Naskinova, "Transfer learning with NASNet-Mobile for Pneumonia X-ray classification," *https://doi.org/10.1142/S1793557122502400*, vol. 16, no. 1, Jun. 2022, doi: 10.1142/S1793557122502400.

[36] M. Elpeltagy and H. Sallam, "Automatic prediction of COVID– 19 from chest images using modified ResNet50," *Multimed Tools Appl*, vol. 80, no. 17, pp. 26451–26463, Jul. 2021, doi: 10.1007/S11042-021-10783-6/TABLES/3.