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LEVERAGING RESNET-152 AND WEB TECHNOLOGY FOR RAPID COVID-19 DIAGNOSIS FROM X-RAY IMAGE

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ABSTRACT

In December 2019, the SARS-CoV-2 virus gave rise to COVID-19, which was first detected in Wuhan, China. The virus has infected over 700 million individuals on Earth. This virus can spread through direct and indirect contact, making humans vulnerable even in small places or through food consumption. The pandemic highlighted challenges, including a shortage of radiologists and the time-intensive interpretation of X-ray images, leading to discrepancies and delays. To address this, a classification model based on X-ray images became crucial for COVID-19 identification. Proposing a web-based system integrating convolutional neural network (CNN) models, particularly the ResNet-152 model, aims to enhance precision in monitoring and diagnosing COVID-19. After fine-tuning a pre-trained ResNet-152 model using transfer learning on a COVID-19 dataset and adding a classification head, a COVID-19-specific classification model is created. In this project, the pre-trained COVID-19 ResNet-152 model achieved 86.84% accuracy, 89.95% sensitivity and 77.27% specificity. The model is then integrated into the system, which enables healthcare professionals to upload and receive a clear visualisation of the COVID-19 classification results via Application Programming Interface (API) endpoints. This platform enables healthcare professionals to login, upload, search, and classify COVID-19 diagnoses based on the uploaded X-ray pictures, providing an intuitive interface and a user-friendly system. Leveraging advanced image processing and deep learning, the system has the potential to expedite accurate diagnoses and alleviate the workload on healthcare professionals, ensuring swift and accurate detection of COVID-19 cases.

Keywords: *COVID-19, Classification, X-ray, ResNet-152 Model, Deep Learning*

1. GENERAL INTRODUCTION

COVID-19, stemming from the novel coronavirus SARS-CoV-2, initiated a global pandemic since its identification in Wuhan, China, in December 2019. In March 2020, the World Health Organization (WHO) declared COVID-19 a Public Health Emergency of International Concern (PHEIC) because of the rapid spread of the highly contagious SARS-CoV-2 virus to nearly every country on Earth [6]. As of October 20, 2023, the virus affected 771 million individuals and resulted in 6.9 million deaths, impacting global health and the economy. The outbreak of COVID-19 caused by SARS-CoV-2 has led to a global health crisis, claiming millions of lives worldwide [5]. Although humans were initially believed to be the primary source of transmission and infection, recent studies indicate that animals, including pets, zoo animals, and certain wildlife species, could also be vulnerable to the virus [11]. According to Abbasi et al. (2022), COVID-19 contamination can spread from humans to food products. Moreover, there is evidence to suggest that some animal-origin food sources, like pigs and rabbits, may also be contaminated. The COVID-19 virus can spread through direct contact with infected individuals and indirect contact with surfaces or objects they use in the immediate environment, as stated by the WHO [14]. Therefore,

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people worldwide are at high risk of contracting COVID-19, even in small spaces or while consuming food products.

The COVID-19 infection typically progresses through three stages: incubation, acute illness, and recovery. During the incubation period, there is a gap between when the patient is infected and when symptoms start to appear. The acute phase is characterized by symptoms like fever, coughing, exhaustion, headaches, congestion, or runny nose. People with mild symptoms can use a COVID-19 test kit to self-check, while those with severe symptoms should go to the nearest hospital for a detailed check, including radiography. In Malaysia, hospitals and clinics use various methods to diagnose COVID-19, including serological tests, molecular tests, real-time polymerase chain reaction (RT-PCR) tests, and antigen tests. According to Kurma et al. (2022), radiography can be used to differentiate between healthy and infected areas of the lungs. Hence, X-ray images can also be used to diagnose COVID-19, with radiographers using visual identification to interpret the images.

The pandemic highlighted challenges due to a shortage of radiologists and the time-consuming interpretation of X-ray images. To address this, developing a classification model using X-ray images became crucial for COVID-19 identification.

Artificial Intelligence (AI), specifically machine learning and deep learning, has demonstrated success in COVID-19 classification tasks. Various Convolutional Neural Network (CNN) models, such as Inception Net, XceptionNet, ResNet, and VGGNet are gaining recognition for their effectiveness. Convolutional neural networks, which are integral in computer vision and radiology, employ convolution, pooling, and fully connected layers to autonomously learn spatial hierarchies of features. Specifically, the ResNet model, chosen for its innovative solution to the vanishing gradient problem, enables effective training of exceptionally deep networks with numerous layers, thereby enhancing performance in complex tasks.

X-ray imaging is a commonly used method for diagnosing COVID-19, favored for its cost-effectiveness, rapid processing, and widespread availability. To leverage these advantages, our study utilizes a ResNet-152 classification model specifically pre-trained and fine-tuned on COVID-19 chest X-ray datasets. This approach not only adapts the model to the medical nuances of COVID-19 but also enhances its ability to extract critical features for accurate diagnosis. After training, the model's performance is rigorously evaluated using key metrics on a separate test set. Building on this foundation, we propose a web-based system that integrates the refined COVID-19 ResNet-152 model. This system is designed with user-friendly features such as X-ray image search, upload functionality, result display, and report generation.

By combining advanced image processing with deep learning techniques, our platform aims to provide rapid and precise diagnostic support, thereby assisting medical personnel in the effective management of COVID-19 cases. This paper details the development process, system features, and the potential impact of our work on public health technology.

1.1 Problem Statement

The prevailing diagnostic approach for COVID-19 relies heavily on the manual examination of chest X-ray images, a method characterised by its time-consuming nature and inherent subjectivity. Healthcare experts must carefully study each image to find potential signs of COVID-19 infection. However, different interpretations of this manual assessment can result in discrepancies and delays in diagnosis [15]. Given the severity and urgency of the current global health crisis, there is an unquestionable need for a transformative solution. Hence, developing an automated classification system driven by advanced technologies like image processing and deep learning becomes imperative. An automated classification system is essential to speed up the diagnosis process, reduce the workload on healthcare professionals, allow them to focus more on critical decision-making and patient care, and ensure fast and accurate identification of cases.

1.2 Objectives

1. To develop a web-based system for COVID-19 classification using X-ray images
2. To implement a reliable and accurate ResNet-based model for detecting COVID-19 in X-ray images
3. To provide clear visualizations of the COVID-19 classification results to enhance user engagement

2. LITERATURE SURVEY

Numerous studies have explored the application of deep learning techniques for classifying COVID-19 using imaging modalities such as X-ray and Computed Tomography (CT) scans. Deep learning is an effective area of Artificial Intelligence (AI) research, which makes it possible to create models that extract features automatically from input and produce desired results. Several

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issues, including diagnosing pneumonia from radiological images [18], detecting breast cancer [16], and identifying possibly benign and malignant skin lesions [17], may be solved with deep learning models. X-ray imaging is commonly used to diagnose COVID-19 due to its low cost, quick processing time, and wide availability [12]. According to Kasban et al. (2015), X-rays use invisible electromagnetic radiation to create images of internal tissues, where different densities allow varying levels of radiation passage. Soft tissues permit the majority of X-rays to appear dark, while denser structures like bones or tumors appear white. However, a CT scan produces detailed images of organs, bones, soft tissues, and blood vessels [13]. An X-ray image is used for COVID-19 diagnosis instead of a Computed Tomography (CT) scan because it generally exposes patients to less radiation, and it is commonly available [22]. The lungs are commonly affected by the COVID-19 disease [7]. Hence, the X-ray image of the lungs is more precise and suitable for a person to obtain the COVID-19 classification result.

In the study of Showkat & Qureshi (2022), they constructed an automatic detection of Pneumonia for COVID-19 diagnosis by investigating several pre-processing and classification approaches, such as transfer learning and deep learning. The customized ResNet model outperforms the existing models with notable results of 95.00% global accuracy, 95.90% sensitivity, and 92.74% specificity [18]. The model is based on ResNet18, enhanced with a dropout layer and Batch Normalization was added to the Fully Connected (FC) layer. The research utilizes a dataset from the public 'CoronaHack-Chest X-Ray-Dataset' on Kaggle. This dataset comprises 5910 unique Chest X-Ray (CXR) images, divided into two clinical categories: 'Pneumonia' with 4334 images and 'Not Pneumonia' with 1576 images. The dataset was partitioned into two distinct sets: 89% for training/validation and 11% for testing. All images were resized to 224x224 and underwent data augmentation, combining affine transformations and color modifications to enhance the dataset and prevent overfitting. This method is relatively fast and straightforward to implement and has effectively expanded the training dataset. Transfer Learning (TL) was employed, using ImageNet weights as initial weights for the ResNet architecture. To ensure optimal performance, model checkpoints were used to save the best weights, and 'Early Stopping' was implemented. This research used binary cross-entropy as the loss function, a learning rate of 0.0001, an Adam optimizer, and a batch size of 64. The customized model was trained with a holdout factor of 35 for 77 epochs.

In Ahamed et al.'s study (2023), a deep learning model for COVID-19 detection using chest X-ray images has been developed. The model is based on the ResNet50V2 architecture, enhanced with six additional layers for robustness and efficiency. The model, fine-tuned for robustness and efficiency, consists of four stages with additional layers, including two dropout layers, two flattened layers, and two fully connected layers. It uses skip connections to address the vanishing/exploding gradient problem. The model is trained with a learning rate of $1x10^{-5}$, a batch size of 32, and 50 epochs, using the SoftMax activation function for multi-class image classification. The model uses Grad-CAM for image interpretation, aiding in early, cost-effective screening of infections by radiologists through a deep CNN model trained on X-ray images. The model was trained on two public datasets with labels for normal, COVID-19, bacterial pneumonia, and viral pneumonia cases **Error! Reference source not found.**[20]. The researchers used a balanced dataset of 4593 images from three public sources, including 1143 COVID-19 images and 1150 images each of normal, bacterial pneumonia, and viral pneumonia cases. The images were pre-processed and augmented to enhance the dataset's diversity. For Dataset-1, 60% of samples were used for training and 40% for testing, while for Dataset-2, all samples were used for training, with 40% also used for testing. The modified model achieved an accuracy of 99.46% for four-class classification on Dataset-2, 97.22% for three-class, and 99.13% for two-class classification on Dataset-1 [2].

The Sreejith & George's study (2021) focuses on the early detection of COVID-19 using chest X-ray images and the ResNet-50 model. The researchers evaluated the performance of the pre-trained ResNet-50 model on a publicly available COVID-19 Chest X-ray dataset consisting of 1000 samples. The model achieved an accuracy of 96% with a 98.00% sensitivity and a specificity of 95.00% [19]. The COVID-19 classification process using ResNet-50 involves several steps. First, images are resized to 100x100 pixels, and the dataset is split, with 80% used for training and 20% for testing. Data augmentation techniques, such as rotation, zoom, and cropping, are applied to enhance the complexity of images and help the model learn more features. The ResNet-50 architecture, pre-trained on ImageNet, is used for feature extraction. The initial layers are retained for this purpose, while the remaining layers are trained to extract features specific to the dataset. Fine-tuning is applied to train

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only the last few layers, making the process faster and more accurate than training from scratch. Lower precision formats than 32-bit are used to reduce memory requirements and shorten training times. Mixed precision, using both 16-bit and 32-bit formats based on computational needs, is also implemented. The model uses an input size of 100x100x3, a batch size of 32, and undergoes a total of 5 epochs in the fine-tuning and training process. This approach allows for efficient and effective COVID-19 classification using chest X-ray images.

With the advancement of technology, AI has found its way into various fields, including the medical field, where it is used to analyse disease causes through deep learning models. Researchers are developing COVID-19 classification models, but these models are not yet being widely used in Malaysia's hospitals and clinics. The proposed system is designed and developed to resolve the problems in the current method (manual examination) and even provide a classification report for healthcare professionals. The manual diagnostic process for COVID-19 using chest X-ray images is time-intensive and prone to subjective variability, which delays diagnosis and increases the burden on healthcare professionals. Existing AI-based solutions are often optimized for general radiological applications but lack customization for COVID-19 classification, leading to suboptimal performance in real-world clinical settings. Some research questions needed to be considered to complete this project. First, how can a customized ResNet-152 model enhance the accuracy and reliability of COVID-19 classification in chest X-rays compared to existing solutions? Then, how can integrating a classification model into a user-friendly web-based system enhance accessibility and utility for healthcare professionals?

2.1 Difference of Existing Systems and Proposed System

Unlike previous studies that primarily employed ResNet-18 or ResNet-50 for COVID-19 classification, this study leverages the deeper ResNet-152 architecture, allowing for superior feature extraction and robustness. In contrast to several research that rely on small datasets, our work used a variety of augmentation approaches to generate a dataset of 17,099 X-ray pictures, assuring robustness and minimizing overfitting. Additionally, integrating a custom classification head and advanced callbacks (early stopping, learning rate reduction) further enhanced model generalization. Incorporating fine-tuning for the last ten layers of the model improved task-specific learning, which has not been explicitly explored in many prior works. Moreover, while others focused solely on accuracy metrics, our study evaluates performance holistically through specificity and sensitivity, addressing clinical diagnostic needs.

3. RESIDUAL NETWORK ALGORITHM

ResNet, or Residual Network, is a widely utilized deep learning model in computer vision applications, recognized for its effectiveness in handling a significant number of convolutional layers within a Convolutional Neural Network architecture. The success of ResNet is demonstrated by its outstanding performance in the ILSVRC 2015 classification competition, achieving a minimal error rate of 3.57% [3]. This achievement highlights the model's effectiveness in image classification tasks. ResNet addresses the vanishing gradient challenge by incorporating skip connection, allowing efficient backpropagation of gradients to previous layers. This distinctive architecture enables the deepening of layers, contributing to enhanced accuracy.

ResNet blocks, typically consisting of two or three layers (ResNet 50, 101, 152), incorporate non-linear activations denoted by "relu" in Figure 1, with their output serving as input for subsequent layers. When combined in a ResNet, these residual blocks effectively learn parameters even in deeper layers, utilizing skip connections strategically to expedite initial training without introducing computational overhead. ResNet models, often with 50, 101, or 152 layers, leverage this design to train deeper networks while maintaining a smooth gradient flow during backpropagation. ResNet's convolutional layers resemble the structure seen in Figure 2. It is a 34-layer ResNet with fully connected layers, padding, and max-pooling for 3x3 convolutional filters. A Softmax Function is used at the end to forecast 1000 classes [10].

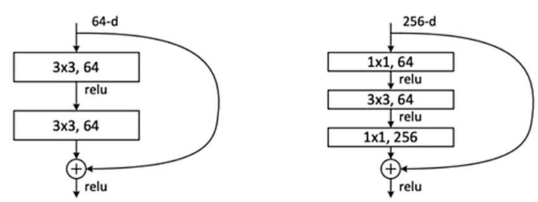

Figure 1: The Architecture Of A Residual Block With Two Layers (Left) And Three Layers (Right)

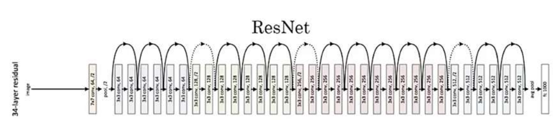

Figure 2: Example Of ResNet-34's Convolutional Layer

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4. EXPERIMENTAL SETUP

The experiment utilized a 64-bit Windows 10 system, employing the Keras 3.1.1 deep learning framework with a TensorFlow 2.16.1 and Python 3.11.8 to construct the pre-trained COVID-19 classification ResNet-152 model.

4.1 Processing and Partitioning of Image

For COVID-19 diagnosis classification, the key element is a dataset of X-ray images. The dataset is augmented for diversity, with an extensive COVID-19 X-ray image dataset obtained from Mendeley Data [4]. This dataset was enhanced with various augmentation techniques to generate approximately 17099 images. The downloaded dataset from this data source consists of non-COVID and COVID cases of both X-ray and CT images, which are separated into two folders, respectively. A subset of 5500 non-COVID and 4044 COVID X-ray images from the downloaded folder is chosen for training and testing the ResNet-152 model. The X-ray images are distributed into 3340 for both COVID and non-COVID sub-folders, respectively, in the "Train" folder. The rest of the X-ray images for both COVID (704) and non-COVID (2160) are distributed into other COVID and non-COVID sub-folders that are in the "Test" folder. Figure 3 and Figure 4 display examples of X-ray images that are included in the dataset.

Figure 3: COVID-19 X-ray Images In The Dataset

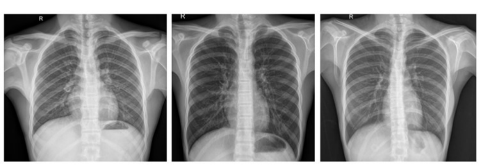

Figure 4: Non-COVID-19 X-ray Images In The Dataset

4.2 Pre-trained COVID-19 ResNet-152 Model

Before training the model, the downloaded X-ray images have been divided into a ratio of 7:3. 70% of images from the dataset are used for the training process, and 30% are used for testing. The ratio of COVID and non-COVID images in the training dataset is equal to ensure that the model does not become biased towards the class with more samples. The image is loaded and pre-processed to RGB format and resized to a consistent size of 224 by 224 pixels using the Python Imaging Library (PIL) library before training to match the size for the ResNet-152 model. Overall, 70% of all images in the "Train" folder were utilized for training, 15% each for validation and testing. TensorFlow datasets are created for each set, enabling efficient batch (32) processing during model training.

The ResNet-152 base model with weights from ImageNet is utilized. The input shape is set to (224,224,3). The base model freezes initially to retrain its learned features while adding a custom classification head for the specific task of COVID-19 classification. The custom layers include a Rescaling layer, a Global Average pooling layer, a Dense layer with 512 units and ReLU activation, Batch Normalization, and a Dropout layer with a 0.5 dropout rate. To avoid overfitting, L2 regularization (0.001) is used for the final Dense layer, which has a SoftMax activation. Figure 5 provides an overview of the architecture of the proposed model.

The model training comprises two stages using the ResNet-152 architecture. Initially, the model's layers are frozen, and it is compiled with an Adam optimizer (learning rate of $1e^{-5}$) and binary cross-entropy loss. Training runs for 25 epochs with early stopping (patience of 5) and learning rate reduction on plateau callbacks to prevent overfitting. The best-performing model is saved via checkpoints. In the subsequent fine-tuning stage, the last ten layers are unfrozen, and the model is trained for an additional 25 epochs with the same learning rate of $1e^{-5}$. This allows the model to learn specific features from the COVID-19 dataset, enhancing its performance. The same callbacks are applied, with early stopping patience increased to 7 and learning rate reduction triggered after three epochs without improvement (reduction factor of 0.2). This strategy ensures efficient learning and optimal model performance.

A COVID-19 classification ResNet-152 model has been saved locally after the training phase has finished for future use. An additional evaluation is conducted on a separate test dataset obtained from a directory, ensuring the model's robustness across different data sources. This dual evaluation of the original test set, and an additional one ensures the model's robustness. The separate test dataset images are standardized to RGB and 224 by 224 pixels for compatibility with the model. Post-evaluation, key performance metrics like accuracy, specificity, sensitivity, precision, recall, and F1-score are computed from the confusion matrix, providing a comprehensive assessment of the model's predictive power.

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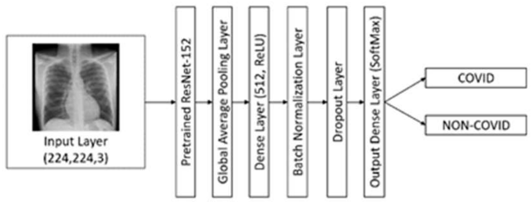

Figure 5: Architecture Overview Of Model

4.3 Load of Model

The trained ResNet-152 model for COVID-19 classification is stored locally and integrated with a Laravel backend for operational use. When a radiographer uploads an X-ray image via the Angular frontend, the image will be sent to the backend through an API. The image is processed using Python Imaging Library (PIL)—converted to RGB, resized to 224 by 224 pixels, transformed into a NumPy array, and normalized. The pre-processed image is then batched and fed into the model for prediction. The output, classified as 'Positive' or 'Negative' based on the predicted probability, is displayed on the front end for the radiographer's review. The confidence percentage will also be shown to the user in the front end.

```
# Load images and labels
for cls_idx, cls_dir in enumerate(class_dirs):
    for img_name in os.listdir(cls_dir):
        img_path = os.path.join(cls_dir, img_name)
        img = Image.open(img_path)  # Load image using PIL
        img = img.convert('RGB')  # Convert image to RGB format
        img = img.resize((224, 224))  # Resize image to (224, 224)
        img_array = np.array(img)  # Convert image to numpy array
        X.append(img_array)
        y.append(cls_idx)  # Assign label based on class index (0 for COVID, 1 for Non-COVID)
```

Figure 6: Image Preprocessing Before Model Training

```
# Split the dataset into training (70%) and testing (30%)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=123)

# Further split the testing set into validation (50% of 30% = 15% of total) and final testing (15% of total)
X_val, X_final_test, y_val, y_final_test = train_test_split(X_test, y_test, test_size=0.50, random_state=123)
```

Figure 7: Data Splitting Into Training, Validation And Testing Dataset

```
# Build ResNet152 model
base_model = ResNet152(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

# Define input layer
img_input = Input(shape=(224, 224, 3))

# Preprocess input using Rescaling layer
preprocessed_input = Rescaling(1./255)(img_input)

# Pass preprocessed input through ResNet152 base model
base_output = base_model(preprocessed_input)

# Use GlobalAveragePooling2D instead of Flatten
pooled_output = GlobalAveragePooling2D()(base_output)

# Add classification head and L2 regularization
x = Dense(512, activation='relu')(pooled_output)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
output = Dense(2, activation='softmax', kernel_regularizer=l2(0.001))(x)  # 2 neurons for 2 classes (COVID, Non-COVID)
```

Figure 8:. Model Architecture

```
# Compile the model with class weights
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=1e-5),
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

Figure 9: Model Compiling

```
# Define callbacks (EarlyStopping and ReduceLROnPlateau)
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)
early_stopping_ft= EarlyStopping(monitor='val_loss', patience=7, restore_best_weights=True)
lr_scheduler = ReduceLROnPlateau(factor=0.2, patience=3, verbose=1)
model_checkpoint = ModelCheckpoint('best_model.keras', monitor='val_loss', save_best_only=True, verbose=1)
```

Figure 10: Callbacks Descriptions

```python
history = model.fit(
    train_dataset,
    epochs=25,
    validation_data=val_dataset,
    class_weight=class_weights_train,
    callbacks=[early_stopping,lr_scheduler,model_checkpoint]
)
```

Figure 11: Model Training

```python
# Fine-tuning: Unfreeze the last few layers of the base model
base_model.trainable = True
for layer in base_model.layers[:-10]:  # Fine-tune all layers except the last 10
    layer.trainable = False

model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=1e-5),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Continue training the model with fine-tuning and class weights
history_fine = model.fit(
    train_dataset,
    epochs=25,
    validation_data=val_dataset,
    class_weight=class_weights_train,
    callbacks=[early_stopping_ft, lr_scheduler, model_checkpoint]
)
```

Figure 12: Model Fine-tuning

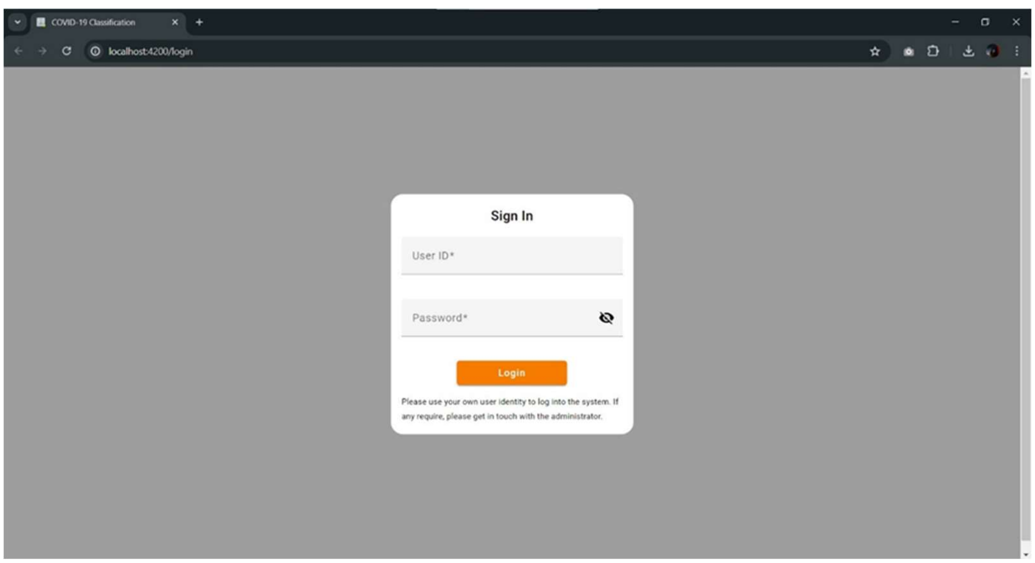

Figure 13: Login Page For Administrator And Radiographer

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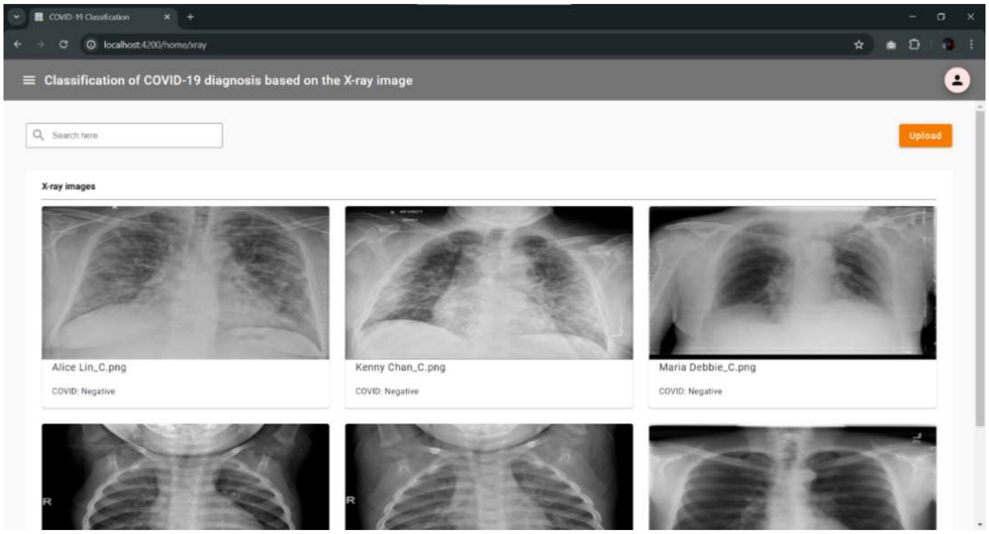

Figure 14: Home Page For Radiographer

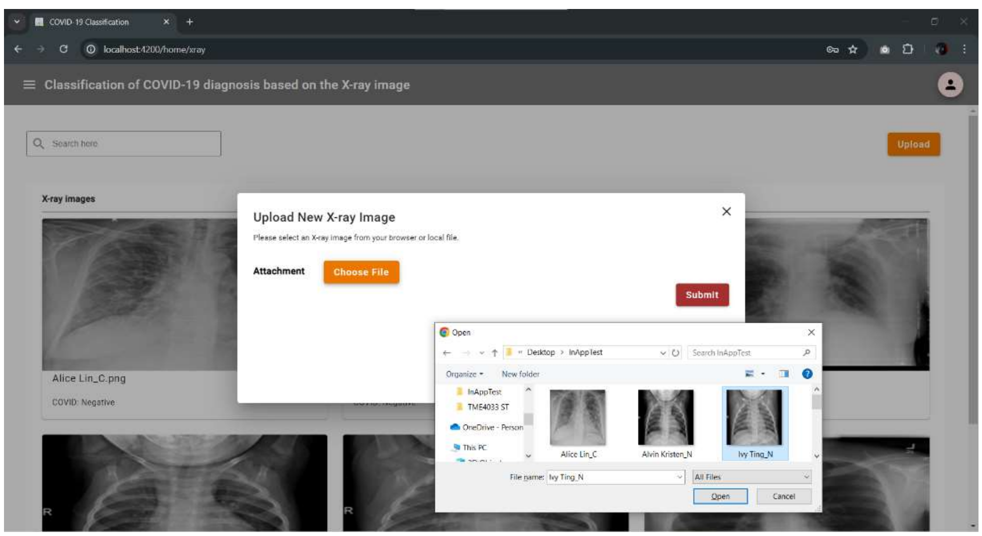

Figure 15: Upload An X-ray Image From The Database

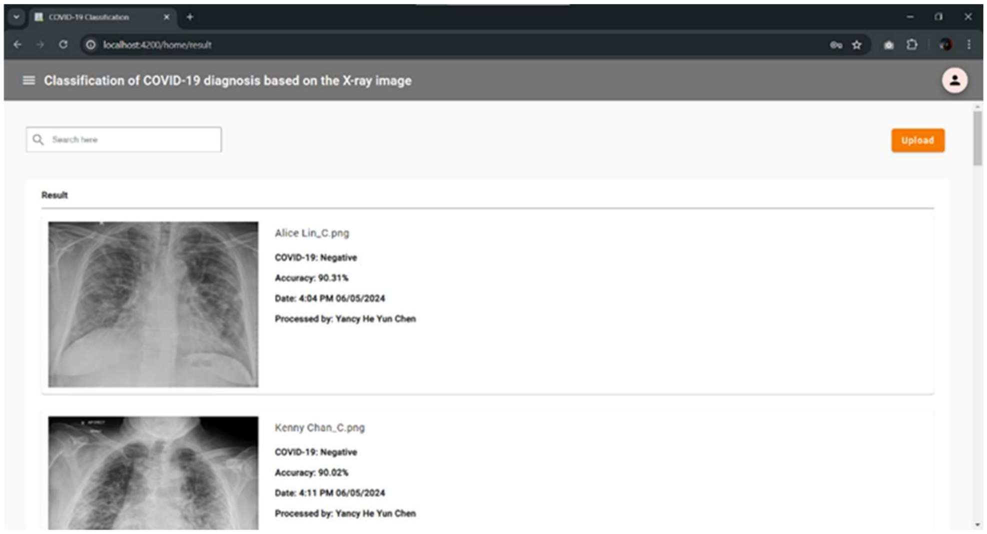

Figure 16: Result Page

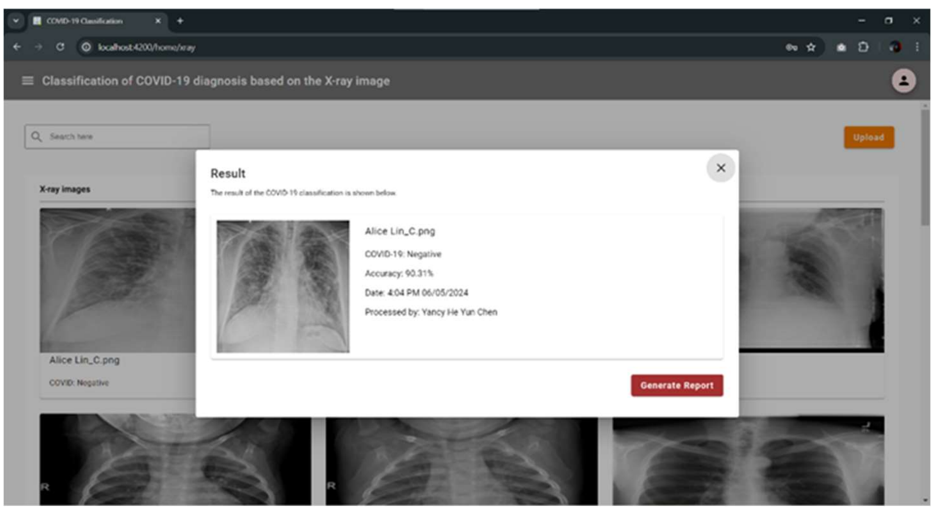

Figure 17: Result Details Page

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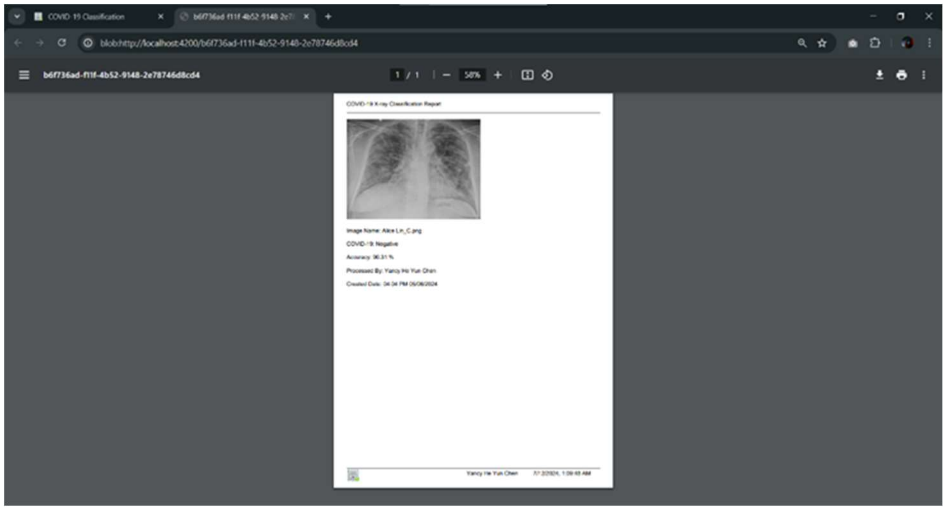

Figure 18: View The Generated Report Page

5. MPLEMENTATION

The pre-trained COVID-19 ResNet-152 model in this study was implemented by using TensorFlow and Keras, which are Python scripts. TensorFlow and Keras are used for implementation, loading pre-trained weights for knowledge leverage. The accuracy, sensitivity, and specificity of the pre-trained COVID-19 ResNet model will be obtained after training. After assessing overall performance, the pre-trained model integrates into the system, enabling healthcare professionals to upload images and receive COVID-19 classification results through API endpoints. For the proposed system, the user interface was displayed in section 5.2. An Angular-based user-friendly interface is designed for radiographers, featuring X-ray image search, upload functionality, result display, and report generation. The Laravel framework manages HTTP requests on the backend, facilitating communication with the pre-trained COVID-19 ResNet-152 model. MySQL serves as the database, storing user data, uploaded images, and classification results. Uploaded images are transmitted from the frontend to the backend via API endpoints and stored in the database. The backend triggers the pre-trained model for image classification, and the result is stored, sent back, and presented to the user for review, then generates the result.

5.1 Proposed Model

The model was developed according to the scripts in Figures 6,7,8, 9, 10 11, and 12 to identify the COVID and non-COVID instances based on the X-ray pictures.

The explanations of the scripts are as follows:

i. The X-ray image from the dataset will be pre-processed to RGB format and resized to a consistent size of 224 by 224 pixels using PIL library as described in lines 31 to 39 (Figure 6) to match the size for the ResNet-152 model.
ii. The “Train” dataset was split into 70% for training, 15% for validation, and 15% for testing by using “train_test_split” with a test_size=0.3 in training. Then, it was further separated to 0.5 (test_size) from the 30%, finally getting a 15% for testing as described in lines 46 and 49 from Figure 7.
iii. In line 60, the ResNet-152 base model with weights from ImageNet is utilized. The input shape is set to (224,224,3) to match the model size.
iv. Based on Figure 8, lines 66 to 78, a Rescaling layer, Global Average Pooling, a 512-unit Dense layer with ReLU, Batch Normalization, a 0.5 Dropout layer, and a final Dense layer with SoftMax activation for binary classification were added to enhance the model. L2 regularization (0.001) is used to prevent overfitting.
v. The model is compiled with an Adam optimizer (learning rate of $1e^{-5}$) and binary cross-entropy loss as described in line 87 to 89 from Figure 9.
vi. From lines 92 to 95 as shown in Figure 10, the details of the callbacks (early stopping, learning rate scheduler, model checkpoint) are described. These callbacks are used to monitor the validation to stop training early and enable the reduction of the learning rate to prevent overfitting.

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vii. In lines 98 to 104 from Figure 11, the model is trained for 25 epochs by training the dataset and validating the model using a validation dataset with early stopping, learning rate reduction, and model checkpoint. The best model is saved.

viii. In the fine-tuning stage (lines 107-122) from Figure 12, the last ten layers are unfrozen and trained for an additional 25 epochs with a learning rate of 1e^{-5}. This step allows the model to adapt and learn task-specific features from the COVID-19 dataset while leveraging the knowledge from ImageNet. The same callbacks are used, but early stopping patience is increased to 7, and learning rate reduction is triggered to optimize learning and performance.

5.2 Screenshots of Proposed System

To run the project, the Python 3.11.8 version must be installed. TensorFlow, Keras, Angular, and Laravel need to be installed in Visual Studio Code.

To run the proposed system, make sure that the Laravel backend and Angular frontend have been served and that Apache and MySQL in the XAMPP Control Panel have been started. In the browser, enter the URL as http://localhost:4200/login to begin using the system.

Figures 13 to 18 are the screenshots of the proposed system that the radiographers are able to use for the COVID-19 classification. The radiographers can log into the system if they are registered in the system, and the user interface is shown in Figure 13. A home page (Figure 14) will be shown to the user after successfully logging into the system. The user can upload a desired X-ray image for classification, as shown in Figure 15. Based on Figure 16, all the results are listed on the result page for view. Figure 17 illustrates the classification and image details when the user clicks the X-ray image on the result page. The radiographer can save and print the generated COVID-19 classification report after viewing the report, as shown in Figure 18.

6. RESULTS AND DISCUSSIONS

6.1. Calculations

Following 50 epochs of training using a dataset of 6680 samples, the COVID-19 classification ResNet-152 model exhibited 86.43% accuracy on the training data and 86.84% on the separate test data. A separate model, which is Model 2, using a different learning rate (1e-4) and total epochs (50), underwent training and testing on the same dataset, and the use of the same model architecture has been developed. Despite the same architecture structure of the ResNet-152 model and using Adam's optimizer, the maximum accuracy attained stood at 86.63%. Table 1 presents a comparative analysis between the proposed model (Model 1) and the separate model (Model 2). This showcases the performance and comparison between the models. Model 1 has better accuracy and sensitivity than Model 2, which states that Model 1 can detect COVID-19 and normal cases more accurately. Figure 19 shows the training and validation accuracy, while Figure 20 shows the training and validation loss of the proposed model across the epochs during the model training process.

Table 1: Performance Matrix Of 2 Models.

Model	Accuracy	Specificity	Recall
1	86.84%	77.27%	89.95%
2	86.63%	77.27%	89.68%

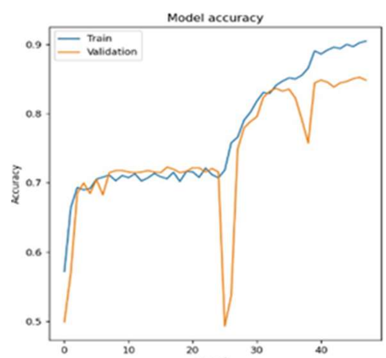

Figure 19: Model's Training And Validation Accuracy

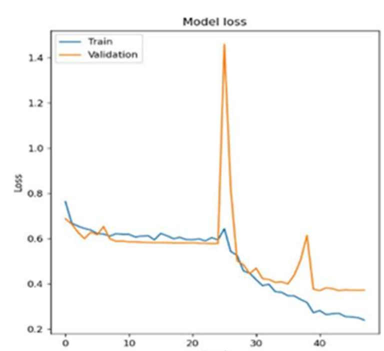

Figure 20: Model's Training And Validation Loss

Based on Figure 21, the proposed model can correctly detect 1943 non-COVID pictures and 544 COVID pictures out of the total of 2160 non-

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COVID and 704 COVID pictures during the testing of the separate test set. 160 COVID sample images and 217 non-COVID sample images were misclassified.

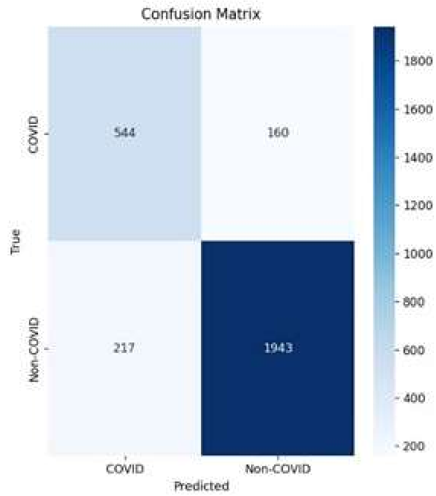

Figure 21: Confusion Matrix Of The Proposed Model

6.2. Error Analysis

Within Figure 17, the proposed model inaccurately categorizes images (a) and (b), leading to misclassifications for the COVID and non-COVID cases. The images are selected to do the analysis because the image's quality is often not in the best condition. The quality of the X-ray images can vary due to technical issues during acquisition, environmental conditions, and patient factors. Image (a), although the actual case of the image is COVID, the classification output from the evaluation is non-COVID, which is Negative. This might be due to the poor contrast and blurriness of the image. Image (b), labelled as non-COVID, showcases a COVID, potentially due to the lighting problem, leading to misrepresentation.


(a) (b)

Figure 22: (a) COVID and (b)Non-COVID, Which The Proposed Model Misclassified

The fine-tuned ResNet-152 model demonstrated competitive performance metrics, including a sensitivity of 89.95% and an accuracy of 86.84%, showing its reliability in accurately identifying COVID-19 cases. A web-based system was developed, enabling healthcare professionals to upload X-ray images and access classification results quickly and efficiently. The system's ability to generate detailed classification reports and confidence scores supports enhanced user engagement and informed decision-making for radiologists.

6.3. Limitations

A few obstacles had to be overcome to construct the suggested system. The proposed system involved the image processing procedure that required high processing to load the entire process. However, the graphics processing unit (Intel (R) UHD Graphics) used by the Acer Swift 5 device will cause the proposed system to have a slower performance, causing the image to load slowly. Since the training time needs longer, the epochs in the training process also face limitations. The processing time grows in tandem with the number of epochs. Furthermore, the approach does not address other pulmonary illnesses such as bacterial pneumonia or tuberculosis; instead, it is limited to binary categorization, distinguishing between COVID-19 and non-COVID-19 instances. Although this decision limits the system's potential for wider diagnostic applications, it does represent a critical need to confront the COVID-19 epidemic. Another limitation is the generalization of the ResNet-152 model. The model's robustness against unseen, real-world datasets from various healthcare contexts is unknown, although it performed well on the dataset utilized in this study. This constraint stems from focusing on a specific dataset to ensure reliable performance within the study's scope.

7. CONCLUSIONS

In this project, a website system that classifies COVID-19 diagnoses based on X-ray images and deep learning architecture, ResNet-152, has been successfully developed. The pre-trained COVID-19 ResNet-152 model achieved 86.84% accuracy, 89.95% sensitivity and 77.27% specificity, validated on a diverse dataset of 17099 X-ray images. The model demonstrates significant reliability in COVID-19 detection, contributing to state-of-the-art medical imaging AI by addressing the vanishing gradient problem in deeper networks. This work significantly contributes to the field by offering a scalable, user-friendly diagnostic tool that integrates deep learning advancements into practical healthcare applications. Unlike similar studies that focus solely on model performance, this research emphasizes system integration and operational utility, bridging the gap between theoretical innovation and clinical needs. This project aims to develop a user-friendly system for classifying COVID-19 using X-ray photographs, implement a dependable and accurate classification model using ResNet for COVID-19 detection in X-ray images, and to clearly visualise the COVID-19 classification outcomes. With the COVID-19 classification ResNet-152 model integration through backend API, the system allows the radiographer to get the COVID-19 diagnosis classification result by uploading an X-ray photograph. The classification result is generated and shown to the radiographer by the system. It is recommended that future work involving multi-class classification be considered to identify different types of lung diseases. Moreover, adding more training and validation sets can enhance the model's generalisation with the use of high-performance GPUs. Additionally, features like profile editing, viewing COVID-19 cases, yearly/monthly reports and account status management can be added to the system to improve its functionality.

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