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Automated Trauma Detection by Using Machine Learning

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Abstract: Imaging techniques are widely used for medical diagnostics. This can sometimes lead to a real bottleneck when there is a shortage of medical practitioners, and the images must be manually processed. In such a situation, there is a need to reduce the amount of manual work by automating part of the analysis. In this study, we investigate the potential of a machine-learning algorithm for trauma detection in medical image processing. A new method called ResNet50V2 was developed on the trauma dataset to detect trauma disease. We compare the results of the new method analysis with other state-of-the-art networks. The proposed base model, ResNet50V2, received a score of 99.40%.

Keywords: *Machine Learning; ResNet50V2; Trauma; Medical Images.*

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I. INTRODUCTION

Post-Traumatic Stress Disorder (PTSD) and acute stress disorder (ASD) are two of the most crippling mental health disorders that can develop after being exposed to horrific events like war, natural catastrophes, accidents, or acts of mass murder [1]. It has long been a problem in both clinical practice and academic research to make a diagnosis of ASD or PTSD. There are many different ways in which trauma-related disorders might manifest, due to the wide variety of risk factors and complicated causes. Diagnostic criteria for classification systems such as the DSM-5 have also been refined through research, including chronic populations and those in tertiary care settings. Nevertheless, the phenomenology of the illness in its early phases can be quite variable and generic, and these criteria might not be able to capture it completely. Cognitive processing therapy and extended exposure therapy have garnered the greatest interest among the evidence-based trauma-focused treatments [2]. It might be tough to create first-line psychotherapies owing to issues like patient burden and varied patient characteristics. Since clinical trial subjects do not necessarily reflect the multimorbidity profiles of "real-life" patients, it is possible that some statistically significant results claimed by evidence-based medicine may not apply to individual patients. This is especially important to consider in PTSD, as research does not always fully address the substantial clinical variability that might be present in this disorder.

Machine learning is a subfield of AI and computer science that teaches computers and other automated systems how to learn from data. It falls under the umbrella of AI and computer science. Because it is able to handle complicated data sets with various distributions and use advanced mathematical approaches, machine learning is useful for building complex data models [3]. Both supervised and unsupervised methods are commonly used in the "learning" process. In supervised learning, the computer learns to convert inputs into desired outputs via methods like regression (where the result is a numerical value) or classification (where the result is a category, like "disease" or "no disease"). Data input and desired results are given to the system by the user. A few examples of popular supervised learning algorithms are logistic regression, neural networks, and support vector machines. One of the most well-known medical applications of supervised learning is the Framingham Risk Score, which is used to diagnose coronary heart disease. Another common use of this method is risk calculation and prediction. While supervised learning relies on predetermined associations and output variables, unsupervised learning seeks to understand the data structure at its core [4]. It can be done via clustering, which finds groups of related cases, or by density estimation, which finds the distribution of the available data. Network analysis, which makes use of regression and clustering techniques, visualizes the connection between individual symptoms and groups of related symptoms, thus providing information on the amount and severity of correlations between symptoms. An up-to-date explanation of

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the relevant machine learning principles and their limitations is available elsewhere.

Improving disease classification, optimizing individualized treatment selection, and predicting treatment results and risk factors are all possible with the use of machine learning methods. Because of the biological and clinical diversity associated with PTSD and ASD, which can impede our capacity to understand their causes and create effective treatments and diagnostic tools, machine learning presents a hopeful avenue for further investigation into these disorders [5].

The most popular diagnostic technique for blunt abdominal trauma (BAT) is computed tomography, which has a big impact on treatment strategies. Deep learning models, or DLMs, have demonstrated significant potential to improve a number of clinical practice elements [6].

Artificial intelligence technology has the potential to address this issue by expediting the diagnosis of these types of injuries and improving patient care and treatment in emergencies. As a result, the medical field is becoming more and more interested in using AI and machine learning (ML) to support physicians. Utilizing AI models as virtual diagnostic assistants to function as secondary image readers can significantly enhance the accuracy and reliability of radiological image interpretation. This gives radiologists more authority and self-assurance in their diagnostic evaluations. Using AI's ability to quickly identify images can speed up the diagnosis procedure and increase clinical effectiveness.

Early and precise injury detection is essential for both successful treatment and patient survival in trauma care. Conventional trauma assessment techniques frequently entail medical professionals' subjective appraisal and manual inspection, which can cause delays and irregularities. The emergence of machine learning holds promise for transforming trauma detection through automation and the use of data-driven insights.

Because they rely on human judgement, the existing trauma detection technologies have limitations that might cause delays and variability in critical care settings. To deliver precise and rapid trauma assessments, an automated system that can evaluate different types of medical data is required.

To create a machine learning-based automated trauma detection system that can effectively identify and categorize trauma cases by processing and analyzing medical data, including imaging scans, patient symptoms, and past medical records. By increasing trauma diagnosis speed and accuracy, this method seeks to improve patient outcomes.

By developing and testing a machine learning-based automated trauma detection system, this study aims to increase the reliability, efficiency, and timeliness of trauma diagnoses. Specifically, this study aims to:

The measurable Contributions of the study with expected results are as under;

- Developed a deep learning method to classify the trauma disease.
- Enhanced the performance of the existing models in terms of accuracy.
- Analyzed the issue of an imbalanced dataset in the context of classification.
- Developed a method to overcome the issues of high false-negative rates.

II. LITERATURE REVIEW

Prior studies have concentrated on automating the assessment of trauma severity and organ segmentation. By utilising a deep learning-based segmentation technique that was strengthened by decision tree analysis, Drezin et al. were able to predict severe artery damage in liver trauma with an accuracy of 0.84. A similar methodology for quantitative evaluation and detection of liver trauma was created by Farzaneh et al., utilising 77 CT scans. Using active contour modelling, Chen et al. developed a four-part approach for the automated grading of spleen damage and automated kidney segmentation in trauma patients. Using a Little dataset and an external attention and synthetic phase augmentation module, Zhou et al. enhanced multiphase splenic vascular damage segmentation using a DeepLab-v3 baseline. Combining shape and statistical data with texture feature extraction has improved the diagnosis of traumatic brain injury (TBI).

By using entropy to extract nonlinear features, Raghavendra et al. were able to identify cerebral haematomas in CT scans with an accuracy of 97.37 percent. He created a model for classifying aberrant CT slices utilising statistical, GLCM, and wavelet data. To classify haematoma subtypes, Sharma and Venugopalan used characteristics depending on shape, texture, and intensity. Tong et al. achieved an 84.86% recall rate using their midline creation technique for identifying haematomas, which involves extracting and comparing LBP texture features and histogram data of both hemispheres. He came to the conclusion that a Bayesian classifier and a distance transform using five landmarks could differentiate between normal and subarachnoid haematomas (SAH), and he suggested a DWT-based paradigm for this purpose in patients with traumatic brain injuries.

Our goal in this research was to determine how well a prototype system based on deep learning could automatically detect rib fractures in trauma CT scans. Algorithm performance was on par with that of radiologists, with a sensitivity of 87.4% and specificity of 91.5% at the per-examination level. As a result of breathing artefacts, normal intercostal arteries, and undamaged ribs, the test generated 0.16 false positives per examination. The F1 score came out at 0.85. There were 587 confirmed fractures out of 894 reports (sensitivity: 65.7%). Fracture displacement and acuteness were the main factors that correlated with the algorithm's accuracy.

Since multiple rib fractures are more common in emergencies than single rib fractures, the algorithm worked better at the per-examination level. Just 9.4 percent of the scans that contained rib fractures in our dataset contained a single fracture. The algorithm's 94.1% NPV proves it is useful as a supplementary reading tool for the pre-exam level.

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Rib fracture detection algorithms using CT images have only been the subject of a single pilot study. Although the number of false positives and false negatives per case was not stated, Yan et al. utilised a CNN and reported a sensitivity of 95.0% and a significantly lower positive predictive value (PPV) of 55.7% for rib fracture identification.

Our findings are consistent with previous research on the effectiveness of algorithms in detecting bone fractures using CT scans. Researchers found 81.3% sensitivity and 2.7 false positives per case when studying the effectiveness of support vector machines for vertebral body fractures. Our study improved the usability of clinical process by identifying fewer false positives per case (0.16). Our results are comparable to those of Bar et al., who also examined a segmentation step and a patch-based CNN for spinal compression fractures; however, they did not provide information regarding false positives. Their study also reported a sensitivity of 83.9% and a specificity of 93.8%.

Also, we found 137 rib fractures that the algorithm had marked several times. Applying this approach at the per-examination level has no major consequences; however, if it is used to precisely count the number of fractures and the results are then confirmed by a radiologist, workflow efficiency may be reduced. False estimates of the frequency of rib fractures may come from blind acceptance of the detailed results without verification.

Although 97 acute fractures were missed in the textual CT reports, the algorithm was able to identify them. Because a higher incidence of rib fractures is linked to a higher death rate, this data highlights the significance of accurate rib fracture identification. Consistent with the results of Ringl et al., we also discovered that the detection rate for anterior fractures was lower than other places. This could be because it is difficult to diagnose the area where cartilage meets ribs.

There have been numerous investigations into feature extraction approaches and segmentation methods for haematoma detection. In order to increase classification performance, many approaches for haematoma segmentation in CT scans use bespoke and handcrafted features. As an example, hematoma regions were segmented using modified DRLSE. The regions were further divided into four classes using shape and texture criteria that were manually created. By analyzing hematomas' shapes, Al-Ayoob et al. were able to create a model that was 92% accurate in classifying them into three categories. Xiao et al. suggested a way to differentiate between subdural and epidural hematomas using main and secondary characteristics associated with the most extensive area of hyper density.

Segmentation is typically approached as a pixel/voxel classification task or utilises classical picture delineation techniques in machine learning algorithms. After that, post-processing methods including active contours, smoothing, morphological operations, and thresholding are applied to each pixel or voxel to extract relevant characteristics. While Farzaneh et al. identified each super-pixel as normal or subdural haematoma (SDH) using geometric, textural, and statistical criteria, Scherer et al. classified haematomas voxel-wise using textural and statistical data. In their work on ICH identification, Muschelli et al. used intensity-feature-based voxel selection.

Various hybrid segmentation algorithms have been put forth, such as active contouring, FCM clustering, region expansion, and thresholding. A wavelet-based thresholding and white matter FCM clustering (WMFCM) model was evaluated by Gautam and Raman, while a nonlinear 3D segmentation method utilising region growth was reported by Saenz et al. The use of FCM clustering and active contour modelling for haematoma delineation was successfully demonstrated by Bhadauria et al. with an accuracy of 99.10%.

By testing MDRLSE with region growth and adaptive thresholding, Prakash et al. demonstrated that it effectively segmented haematomas in 3D CT images. Using an autoencoder trained to identify haematoma slices, Nag and colleagues demonstrated a cost-effective haematoma segmentation approach with a sensitivity of 0.71.

Critical findings in CT scans can now be detected and classified using deep learning algorithms, according to current research. A deep learning-based approach for key finding identification, such as infarcts and haematomas, was introduced by Prevedello et al. A 3D convolutional neural network (CNN) model for CT result triage and classification was created by Titano et al. using ResNet-50. To merge slice-level classification with context, Grewal et al. developed a RAD net, which achieved an accuracy of 81.82%. Using a U-Net based architecture for localisation and classification, Chilamkurthy et al. utilised deep learning algorithms to detect and confirm abnormalities in non-contrast head CT scans.

III. METHODOLOGY

A. Materials and Methods

This study introduces a machine-learning approach for trauma disease classification. Classification of trauma diseases affecting the mind using a machine-learning approach is presented in this paper. A first-level augmentation and pre-processing stage is applied to generate distinct records and address the class imbalance. After mechanical features were extracted to differentiate between trauma diseases from the dataset, a pre-trained "Machine Learning Method" model was applied at the second level. Figure 1 shows the steps involved in the suggested method's process flow.

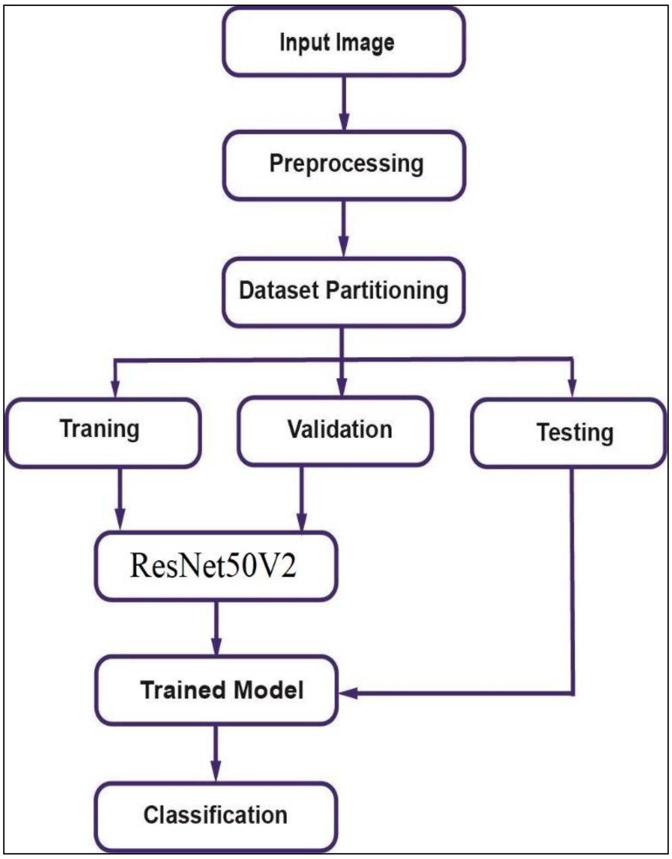

Fig 1 Flow Chart of the Presented Method.

B. RSNA Abdominal Trauma Detection Dataset

The effectiveness of machine learning methods depends heavily on the availability of a good dataset. The most extensive collection of high-quality trauma disease images made accessible for study can be found in the RSNA Abdominal Trauma Detection Diseases dataset archive [28]. There are 186K images in the dataset.

C. Image Pre-Processing

Preprocessing is applied to all input photos of the RSNA dataset to achieve increased consistency in classification results and enhanced feature extraction. A massive image dataset was needed for the CNN approach's extensive training repetitions to avoid the risk of over-fitting.

All photos in the original RSNA dataset can be found in a resolution of 6000 × 4000 pixels. To hasten the process with Python code, the dataset is downsized to 224 x 224.

We have utilized the Image Data Generator function of the Keras library in Python to enhance the data in multiple ways, preventing overfitting and expanding the training dataset. Keeping the same range of pixel values allowed us to cut the computing cost by utilizing a scale transformation. Consequently, a 0–1 range for pixel values was established using the parameter value (1. /255).

The images were rotated by a fixed amount (25 degrees in this case) using the rotation transformation. With the width shift parameter set to 0.1, the images were shifted randomly to the right or left using the width shift range transformation. Using the height shift range option with a value of 0.1, the training images were vertically flipped. A shear angle of 0.2 was used in this case; this is a method for image transformation wherein one axis is kept constant while the other is extended. A zoom range of 0.2 was utilized to enlarge the image, in accordance with the rules of random zoom transformation: a value greater than 1.0 indicates that the images were enlarged, and a value less than 1.0 indicates that the photos were zoomed out. Using the flip function, we were able to modify the image's horizontal orientation. We used a scale where zero is totally black and one is really light to change the brightness.

We trained ResNet50V2 from the ground up using the dataset from the last chapter. The RSNA dataset was divided into three parts: training, testing, and validation. After training on the training set, the ResNet50V2 model was tested and evaluated using the validation and test datasets. As a result, we split the dataset between training, testing, and validation, with 60% going to each.

Scaling, rotating, brightening, height shifting, zooming, shear-ranging, horizontally flipping, and channel-shifting with fill mode closest were all used to extend the training set in order to increase the dataset size and diversity. Eliminating overfitting would guarantee that the model can be applied to new situations. Model optimization was employed in the study process. Training images with 60% image ratios were utilized in the current study using the RSNA dataset. Twenty percent of the remaining forty percent of the actual photos go into testing and validation. With the use of ResNet50V2, the model was taught to classify and forecast the labels of each training image.

D. Architecture of ResNet50V2

The ResNet model [29] is well-known and widely used in computer vision competitions due to its consistently excellent performance. Many more exist; for example, Inception ResNetV2 [30], Mobile Net [31], and Google Net [32]. These models are educated using information from numerous photos across various datasets. To effectively address a wide variety of computer vision problems, transfer learning methods can take advantage of these pre-trained model weights (dataset and computing resources). The ResNet50 model was pre-trained on a small dataset of plant species images for transfer learning. Subsequent paragraphs will delve into the specifics of the ResNet50V2 model's architecture and the many pre-trained weights it can draw from. The ResNet50V2 model is a fifty-layer convolutional neural network (CNN). Figure-2, depicts the architecture of the ResNet50V2 model, including the ResNet50V2 fine-tuning setup.

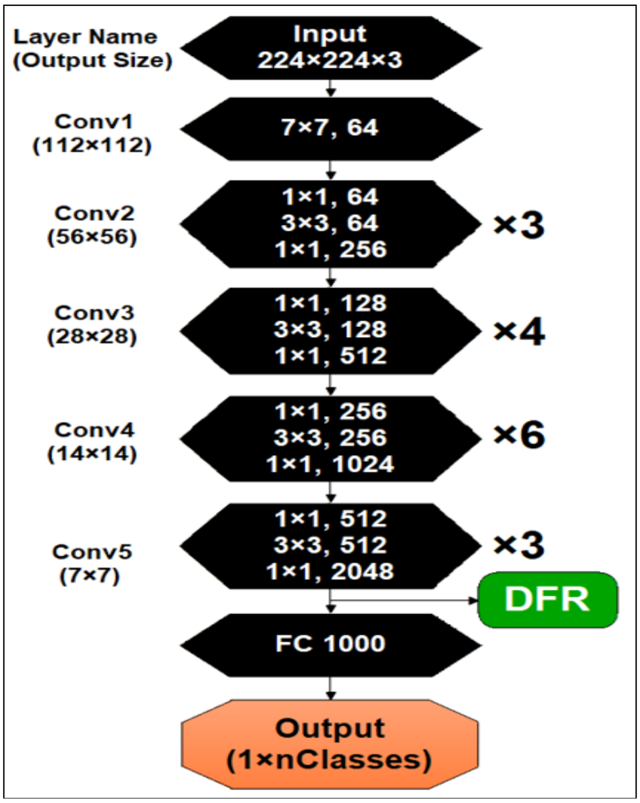

Fig 2 Architecture of the ResNet50V2 Model.

E. *Evaluation Measures*

The testing dataset was used to evaluate the suggested approach following the training phase. We tested the architecture's efficacy using recall, accuracy, F1 score, and precision. We will examine the performance metrics utilized in this research in the parts that follow. What follows is a mathematical definition and representation of the terms "true positive," "true negative," "false negative," and "false positive."

➢ *Classification Accuracy*

The accuracy of a classification system can be evaluated by determining what percentage of its predictions were correct and what percentage were incorrect.

Accuracy = T P+T N / (T P+T N +FP+FN)

➢ *Precision*

When analysing the effectiveness of a model, classification accuracy may not always be the most appropriate metric to employ. For instance, this is one of the scenarios where there is a considerable gap in socioeconomic status. It's a safe bet to assume that each sample is of the highest possible quality. If the model isn't picking up any new information, it would be irrational to infer that all components belong to the best class. Therefore, when we talk about accuracy, we refer to the fluctuation in findings you receive while measuring the same object several times with the same tools. The term "precision" refers to one of these statistics and can be defined as follows:

Precision = T P / (T P+FP)

➢ *Recall*

Another critical parameter is called recall, and it refers to the percentage of input samples that are of a type that the model can accurately predict. The formula for the recall is as follows: Recall = T P / (T P+FN)

➢ *F1 Score*

The f1 score is a statistic utilised to contrast recall and precision.
F1 Score = 2 * (Precision * Recall) (Precision + Recall)

IV. RESULTS AND DISCUSSION

A Google Research team evaluated the ResNet50V2 model. This ResNet50V2 method experiment was built using Tensor-Flow, the free and open-source Keras, and Python. There was a default learning rate and a binary cross-entropy loss function used during training by the Adam optimizer.

- Automated Trauma Detection by Using Machine Learning was observed using the RSNA dataset to assess its efficacy.
- Evaluation of the presented ResNet50V2 model's performance on the RSNA dataset using data augmentation techniques on the training set.
- The results were compared to those of other state-of-the-art networks.
- To evaluate the results of Trauma disease classification prior studies using machine learning.

A. *Performance of Proposed Model on RSNA Dataset*

We evaluated and analyzed the performance of the ResNet50V2 base model on the RSNA dataset. Validation accuracy for the model increased from 99.87% at the end of the first epoch to 99.67% after the most recent epoch. Training accuracy improves from 96.85% after the first epoch to 99.45% after the last epoch in Figure 4.1. As seen in Figure-3, ResNet50V2's validation loss drastically decreased from 75% to 1.34%. Furthermore, similar to the initial loss, the training loss was 9.78% after the first period and 1.76% after finishing training.

On a previously unseen test set, the ResNet50V2 base model was evaluated. While the model's overall accuracy was 99.40% across the board in the test set, ResNet50V2 excelled in the trauma class, achieving 99% precision, 100% recall, and 99% F1-score. The typical class is first-rate, with a flawless 99% recall, 100% accuracy, and 99% f1 score.

Using a confusion matrix, we could visually examine how well various models classified data. The rows of the confusion matrix that are not on the diagonal represent the inaccurate predictions. Classification accuracy in the related ResNet50V2 base model was shown by darker colours, whereas misclassified data was shown by lighter colours. Figure-4 shows the confusion matrices from the test set that will be used to evaluate the overall effectiveness of ResNet50V2. The confusion matrix shows that the ResNet50V2 baseline model's predictions were correct for all picture categories. Confusion analysis using the default ResNet50V2 model settings reveals a data identification success rate of 99.40% and a false positive rate of 0.60%. The ResNet50V2 base model does a fantastic job when comparing the trauma and normal samples' confusion matrices.

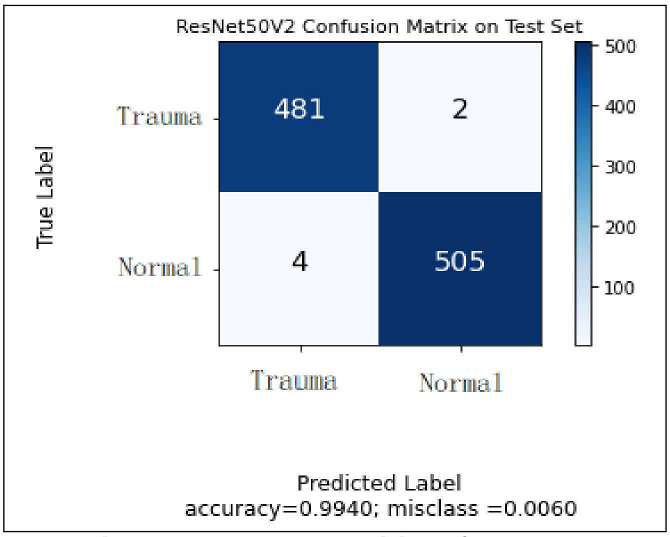

Fig 4 The ResNet50V2 Base Model Confusion Matrix on Test Set.

V. CONCLUSION

The research described in this manuscript explored using Convolutional Neural Networks to recognize trauma in real-time using machine learning techniques. For trauma detection, this method is both reliable and quick. The test findings demonstrate a remarkable accuracy rate in identifying people who are either trauma disease or normal. The trained model completed the task using the ResNet50V2 model, with individual accuracy results of 99.40%.

The best way to train a CNN model to identify and recognize trauma diseases in humans is to integrate multiple models and evaluate their performance accuracy. In addition, the authors recommend an improved optimizer, more precise parameter values, enhanced tuning, and models for adaptive transfer learning.

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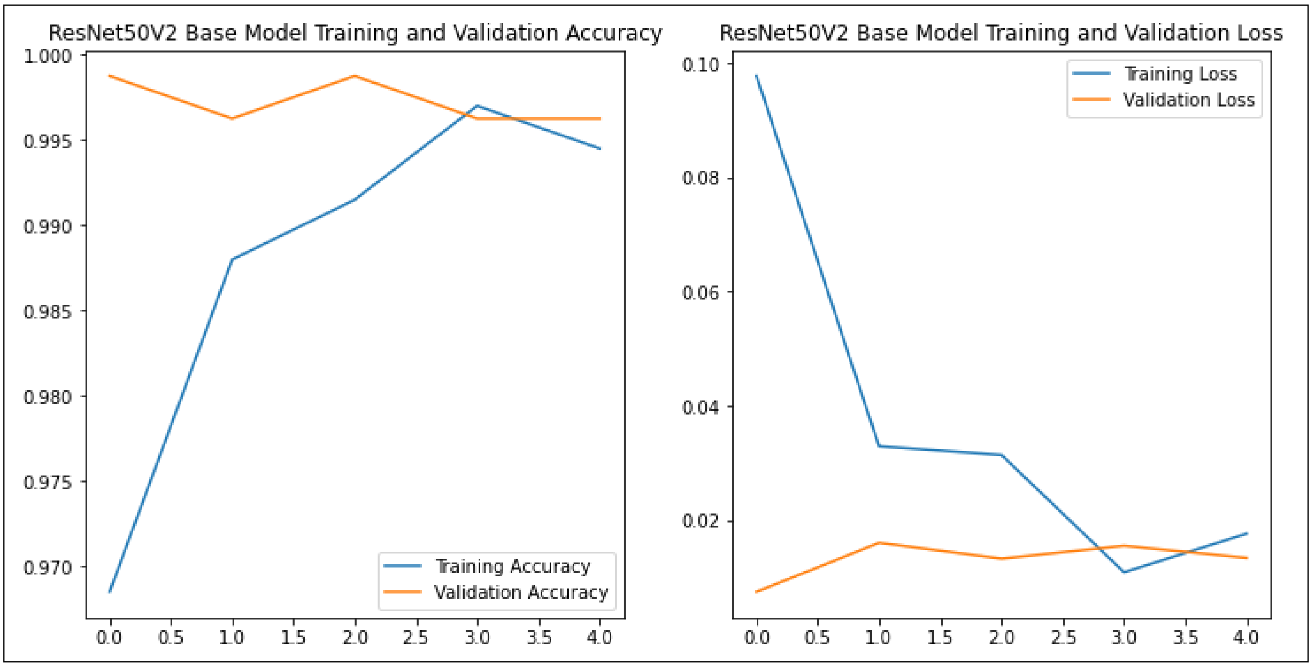

Fig 3 The ResNet50V2 Base Model: (a) Accuracy (b) Loss Graph.

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