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Research Article

Comparing Optimization Algorithms For Enhancing Resnet152v2 Performance

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ABSTRACT

Background: While Convolutional Neural Network (CNN) methodologies have widened to include ensemble and the generation of models from the original individual CNN designs, very few research have compared how well these approaches perform when it comes to recognizing and localizing rice diseases. But a lot of people are unaware of the differences between mutton, hog, and beef. The current study uses the ResNet152V2 algorithm to categorize multiple types of beef, mutton, and pork.
Aim: To correctly prepare ResNet152V2, measure the computing assets (e.g., memory use, training time) needed by any optimization procedure.
Method: In the proposed approach, a previously trained Convolutional Neural Networks, architecture is used to extract parameters from a dataset of a mammogram image analysis for left-right comparison. ResNet152V2 is then deployed to distinguish among the four kinds of mammograms (A, B, C, and D).
Results: The results of the trial demonstrate that ResNet152V2 allows for comparison types with an incredible 100% overall accuracy, supporting the model's suitability as a mammography type recognition and classification tool.
Conclusion: Thus, our research provides strong support for the use of ResNet152V2 in the broader context of breast cancer detection and diagnosis.

Keywords: Convolutional Neural Network (CNN), Accuracy, Resnet152v2 Algorithm, Breast Cancer Detection, Mammographic Image.

I. INTRODUCTION

Since Human–Computer Interaction (HCI) benefits society as well as advances technology, it is one of among the most significant study topics. Every industry, including healthcare, education, aerospace, information technology, consumer discretionary, and telecommunications is affected by HCI. One area of HCI with a wide range of uses is gesture recognition. A gesture-recognition technique called sign language recognition (SLR) is used for picture scaling, gaming interfaces, [1], computer and phone system control, and controlling devices like TVs and robots. These apps all involve processing images or videos, which means they all need a lot of visual processing. Sign language has been utilized by deaf populations to communicate both within and outside of their group. Unlike the language of speech used in everyday conversation, [1, 2], it is an image-based language that relies on hand, body, and facial gestures. Communications between the hearing and the deaf must be maintained via the translation of the sign language into speech or text. Since the 1970s, there has been a significant increase in the use of Machine Learning (ML) techniques and hand-crafted features for gesture detection, especially SLR. In Deep Learning (DL), Convolution Neural Networks (CNNs) rapidly replaced mechanical findings and Machine Learning (ML) treatments with a more efficient, automated, quicker, and better extraction and sorting of features approach.
For gesture recognition, researchers additionally employ a variety of data formats, including RGB, depth, and skeleton. Skeletal data comprises the different joint positions of an individual human body, whereas depth represents the distance of the item from the imaging device or sensor. Based on the period-of-flight concept, Microsoft introduced KinectV2 in 2014 [3]. This device determines the depth by calculating the round trip

duration of a light transmission using an LED or laser. Because it can record all three forms of data, this camera is widely used in computer vision [3, 4]. Numerous studies that used CNN and the aforementioned data types to recognize sign language are documented in the literature; these studies outperformed the most recent machine learning approaches.

According to its delayed discovery, cancer is considered one of the most dangerous and genetically damaging illnesses in existence today [4, 5]. The diagnosis may be made by using cutting-edge imaging methods, reviewing the health records of the individual, or witnessing the signs and symptoms. Of them, imaging has been shown to be the most accurate way to diagnose a patient [5, 6]. In this process, machine learning is essential because it provides medical professionals with critical information so they may make well-informed decisions.

A particular kind of x-ray called a mammogram is used to examine breast tissue. They are performed using an instrument that has two specifically designed plates on it. This device differs from typical x-ray equipment in that it utilizes less radiation. Mammography may help in early detection of tumours in the breast, which occurs often before the disease's symptoms are recognized by medical professionals [5, 6]. This enables the early detection of breast cancers, when they are most treatable. X-rays are used for medical treatment [7].

The most common sign of cancer is the body's aberrant cell multiplication, which may spread throughout the body. More than a hundred forms of cancer, most famously breast cancer, have been found. A malignancy is another term for it. Cancer symptoms are varied and mostly depending on the particular form of cancer, making diagnosis and detection very difficult. The early therapy that is essential for patient survival has been hampered by this problem. Chemotherapy, radiation, and surgery are often used in cancer treatment [7, 8]. The profession has adopted Computer-Aided Detection (CAD) because to the limitations of mammography. This technique reduces the possibility of human mistake by offering a trustworthy, computationally second opinion, which helps radiologists interpret pictures more precisely.

In 1998, the US Food and Drug Administration, [9, 10], or FDA, authorized CAD because to its effectiveness and reliability. Today, treatment facilities and medical facilities all around the world use it extensively. Research is now being conducted to investigate the efficacy of CAD in breast cancer imaging screening as well as its influence on radiologists' performance. The use of computers in radiology diagnostic processes has greatly helped radiologists and improved patient diagnosis reliability [10, 11]. The widespread utilization of software programs for use in healthcare institutions has greatly enhanced the capacity of radiologists to undertake diagnostic screenings, particularly in identifying anomalies in the chest cavity of female customers. Computer-Aided Detection (CAD) is a computer-assisted technique that uses specialized software to discover physical irregularities and aid radiologists in the interpretation of images [12, 13]. This reduces the likelihood of false-negative the results, which might jeopardize the patient's health.

Still, there are definitely certain disadvantages to the approach. Accurately interpreting the pictures may take radiologists some time, and the images under analysis may be impacted by complicated physical characteristics that cause tissue overlap in x-ray projections. The anatomy of the breast, breast density, and the radiologist's education and experience all affect how accurate a mammogram will be [14, 15]. Remarkably, 30% of overlooked lesions and 70% of missed cancer in women identifications in secondary readings are caused by insufficient interpretation of data.

The main objective of this study is to improve mammography-based techniques for breast cancer early detection and diagnosis. The wider use of Computer-Aided Detection (CAD) may be significantly enhanced through early screening, categorization, and the segmentation of breast cancer. Deep learning is a powerful tool in the battle towards breast cancer, particularly when it comes to primary diagnosis and classification [16, 17]. Along with a host of other accessible procedures, MRI, CT scan, and mammography comprise three of the most often used tools for diagnosing and diagnosing individuals with breast cancer. Long detection times are a major drawback of current CAD systems, making them unsuitable for use in actual hospital or laboratory environments. While attaining instantaneous identification, some CADs make accuracy compromises [18]. Comparing the Convolutional Neural Network (CNN) to other conventional approaches, on the other hand, shows that CNN has the greater ability to provide outcomes that are noticeably better. The tedious process of creating features by hand has been replaced by the astounding advances in deep learning models. Rather, [18, 19], a model that utilizes deep learning finds and learns the most important characteristics that apply to our situation automatically, making it possible to find the tumors that are needed.

A further advantage of deep learning models over conventional ones is their capacity to learn at several levels of representation. As a consequence of this, deep models are able to learn a wide range of data representations. The learning process starts with raw data and continues through greater degrees of abstraction until a perfect visualization is reached.

The suggested approach consists of three techniques. Our approach initially uses the Convolutional Neural Network (CNN) technology for both left and right mammograms, correctly bending and scaling the pictures to locate masses. The next approach determines the difference between dangerous and innocuous breast cancer by analysing the various kinds of picture brightness in the mammography dataset using ResNet152V2 [19, 20]. The third method involves differentiating between several types of unnatural mammograms and use a comprehensive identification and categorization system that utilizes Mask R-CNN to identify benign and malignant tumour's as well as quantify the size of the cancer location. The capacity of Mask R-CNN to carry out accurate tumor identification and instance segmentation concurrently is a major benefit of adopting it in this investigation. In this specific scenario, when precisely determining the borders of tumors inside a picture is essential for both diagnosis and treatment planning, this capability is very helpful [20]. Mask R-CNN is able to predict segmentation masks in addition to object boxes with boundaries, which allows it to deliver more precise information on the position and size of tumors in an image.

1.1 Objectives of the study

- Study how well the improved models generalize to new data by running tests on test and validation sets from other datasets or domains.

Provide a thorough analysis of various optimization techniques, stressing their advantages, disadvantages, and applicability for ResNet152V2 training on certain tasks or datasets.

- Examine the optimization algorithms' training trajectory and loss landscape to learn more about the way they operate and their characteristics.

II. LITERATURE REVIEW

(Breve, F. A. 2022) [21] Following just over four months before its first discovering things COVID-19 rapidly spread over the world and became a pandemic. To stop this illness from spreading, it is imperative that it be discovered as soon as possible. An efficient screening method that was added for the Reverse Transcription-Polymerase Chain Reaction (RT-PCR) was the use of Chest X-Ray (CXR) images. Convolutional Neural Nets (CNNs) are an efficient instrument for CXR diagnostics and are often used for automated picture categorization. In order to detect COVID-19 in CXR pictures, 21 alternative CNN architectures are evaluated and compared in this work. The COVIDx8B data set, a large COVID-19 database including 16,352 CXR pictures from patients in at least 51 countries, was subjected to their application.

(Yadav, S. S., Sandhu, J. K., 2020) [22] The endeavour aims to solve the issue of image identification challenge using deep neural network models. These days, a dangerous coronavirus illness known as COVID-19 sickness threatens every person. The global economy is impacted by the coronavirus outbreak in a number of countries. The rapid identification of COVID-19 patients is crucial to preventing the virus's transmission and social impact. Chromatography (CT) scans and pathological testing are useful in the diagnosis of COVID-19. However, there are a number of drawbacks to these tests, including a high rate of false positives and very high costs. Therefore, it's necessary to identify a quick, accurate, and affordable method for detecting the dangerous COVID-19 virus. A chest x-ray may be helpful in identifying this illness.

(Valarmathi, B., Gupta, N. S., 2023) [23] The use of computer vision techniques and deep learning will be used to identify the breed of dog from a picture. The thought is for the client to give an image of a canine, and the PC model will recognize the variety by choosing one of the 120 varieties remembered for the dataset. Xception, among VGG19, a NASNetMobile, EfficientNetV2M, ResNet152V2, Crossover of Beginning &Xception, and Mixture of EfficientNetV2M, NASNetMobile, Sleep deprivation &Xception comprise a couple of the calculations in view of profound learning utilized in the proposed study to foresee canine varieties. The ongoing framework utilized ResNet101, ResNet50, and InceptionResNetV2, and Beginning, rendition 3, on the Stanford College Canines Standard Datasets.

(Gopala Krishnan, B., 2021) [24] The total number of persons using multimedia has grown recently. Long-term exposure to these streams may induce eye discomfort, which can result in dry eyes, headaches, and blurred vision. The proposed method uses a transfer learning model with convolutional neural networks to identify eye strain from retinal pictures. Pre-trained models, such as the beginning V3 and Resnet152V2 architectures, are used for picture training and testing in order to diagnose eye conditions. Using these two architectures, each transfer approach to learning is combined with an optimization method, like Adam, to determine the disease's stage.

(Verma, S., Gopal, D. G., 2023) [25] Pneumonia is the most common lung illness affecting individuals globally. It might be difficult to diagnose pneumonia just based on a Chest X-Ray (CXR). The goal of the project is to make pneumonia infection diagnosis easier for both specialists and beginners. We propose a Deep Learning (DL) method for Transfer Learning (TL)-based pneumonia identification. The suggested approach recovers picture characteristics using a residual network that was previously trained on ImageNet, and then feeds that information into a CNN classifiers for prediction.

III. DATASET

Film screens radiography and the digital mammography are two of the mammography procedures. Full-Field Digitally Mammography (FFDM) is another term for electronic mammography. In this study, [26], Figure 1 and digital mammography have been developed on [19]. The dataset consists of 510 photos from 255 people, 133 of those have carcinoma and 117 of whom only have lumps. Each patient has two photographs in the dataset.

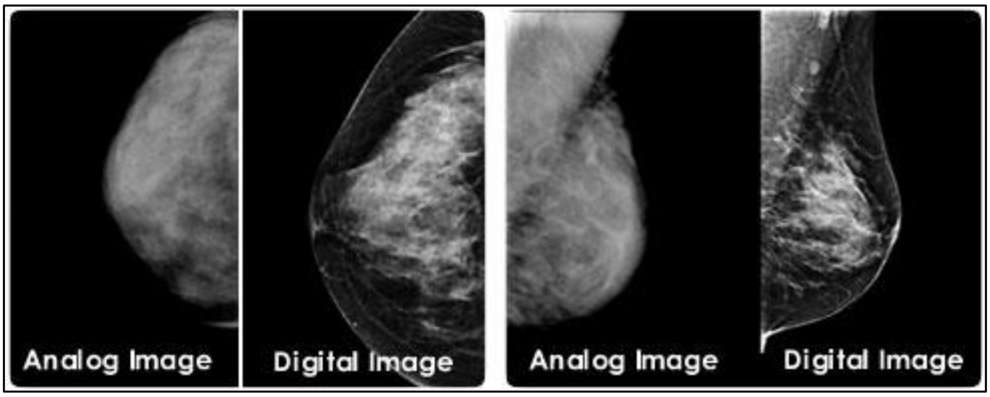

Fig. 1 Screen-film mammography combined with digital mammography.

The method described above uses several convolution approach layers to create a new, straightforward CNN model with six layers and an impressive precision of 99.3%, as shown in Figure 2.

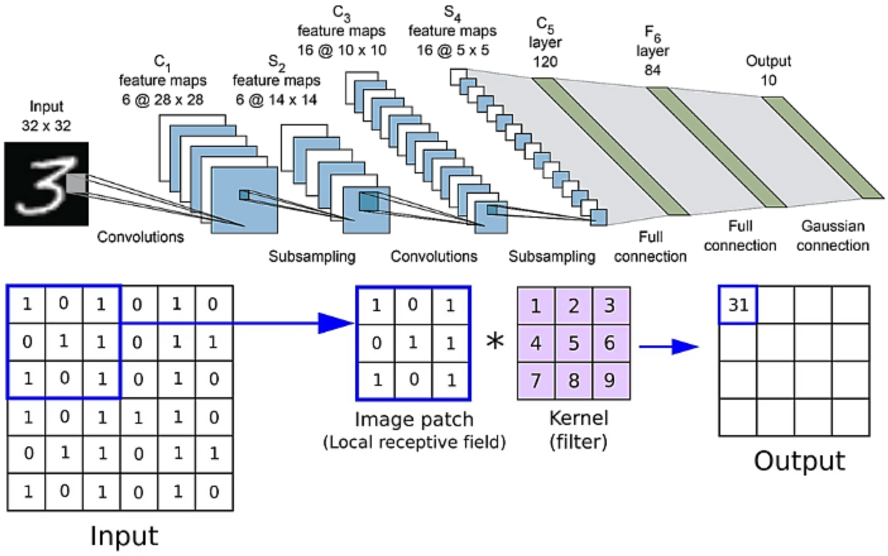

Fig. 2 One-layer convolutional neural network (CNN) structure.

A completely novel deep CNN architecture called ResNet152V2 was recently unveiled [25, 26]. Lately, architecture has been frequently employed in medical imaging applications Figure 3.

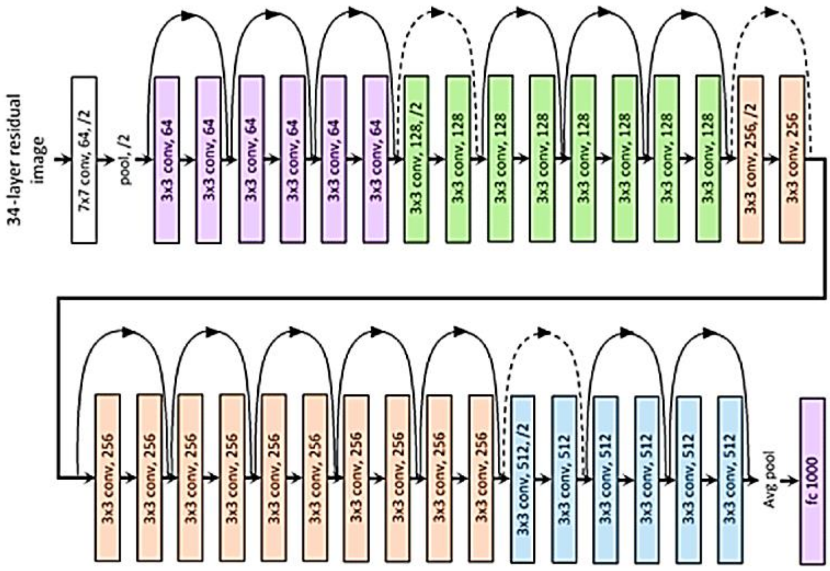

Fig. 3 Architecture of ResNet152V2.

As a method to make the distinction between benign and malignant objects in an image, this work used Mask R-CNN for the identification of objects, as shown in Figure 6.

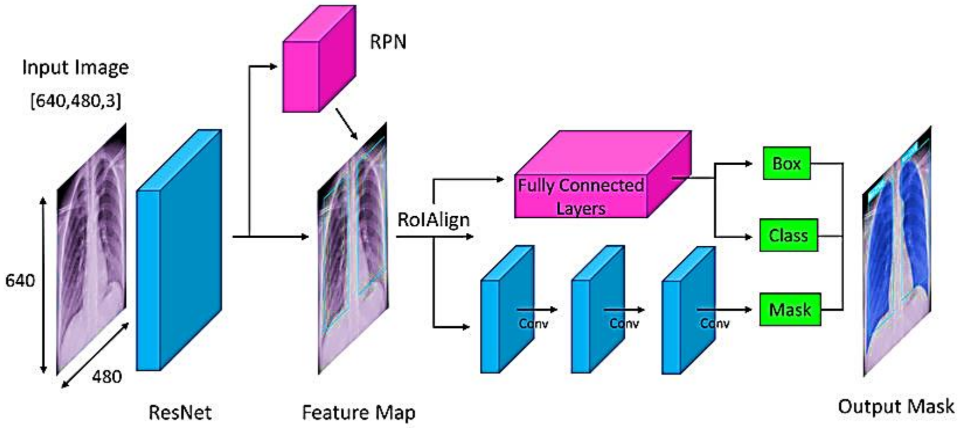

Fig. 4 R-CNN Architectural Shield.

IV. METHOD

Treatment of breast carcinoma at its early stages is now attainable due to early detection. An independent, multicentre dataset was employed to investigate a company's Computer-Aided Detection (CAD) system in breast cancer research [27]. The findings indicated that the system identifies a greater percentage of breast cancers that appear as lumps.

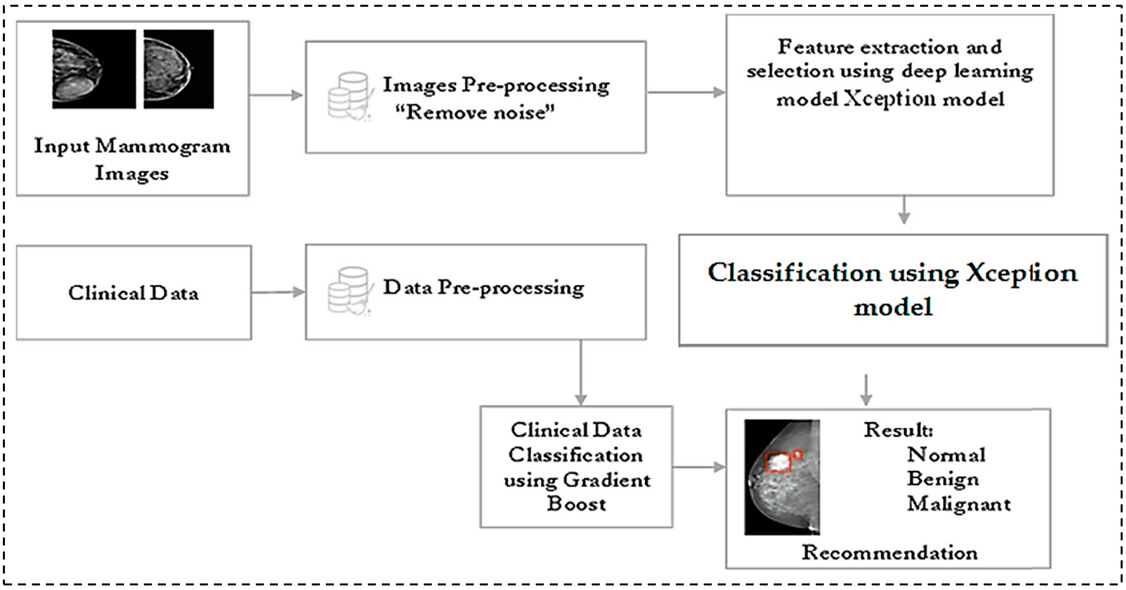

Fig. 5 Identified Model.

The Integrated Development Environment, or IDE, for the Python programming language is called PyCharm. The hyper parameters used utilized by the Tensor Flow-based Mask R-CNN structure are provided in Table 1. Table 1 Based on Tensor Flow, Mark R-CNN.

Batch size	1
Detection_max_instances	100
Detection_min_confidance	0.7
GP_count	2
Images per unit	3
Learning rate	0.002
Num of class	2
Steps per epoch	101
Weight decay	0.004

Validation steps	40
Use mini mask	True

V. RESULTS AND DISCUSSION

Initially, characteristics were chosen for the current research from the dataset that was gathered at the hospital. Three element determination calculations — CNN, ResNet152V2, and Cover R-CNN — were then utilized. Three models are often used in the system for breast mammography images.
The rate of movement of precise gauges is represented by the Accuracy (CA). It is calculated by taking the total number of accurate predictions and dividing it by the total number of times the events occur.

$CA = \frac{TP+TN}{TP+TN+FP+FN}$ 1

Precision, otherwise called positive prescient worth, is the capacity to perceive which of individuals who were thought to be positive are truly certain. It is determined by deducting the all-out number of genuine up-sides from the all-out number of genuine positive and phony up-sides.

$precision = \frac{TP}{TP+FP}$ ...2

The amount of actual positives that were, as of yet, exactly unknown to consciousness is the true positive rate. It very well may be determined by deducting the complete number of positive results from the absolute number of genuine up-sides and tricky negatives.

$Sensitivity = \frac{TP}{TP+FN}$ ...3

Explicitness is a defining characteristic of the actual regretful rate. This is the exact amount of real drawbacks that were calculated. To accomplish this action, we divide the total number of false positives by the total number of real negatives and false positives.

$Specificity = \frac{TN}{TN+FP}$ ...4

The F1-Score is the symphonises mean of exactness and review. When compared to the CA, it provides a more precise indication of the instances that were incorrectly categorized.

$F_1 = 2.\frac{precision.sensitivity}{precision+sensitivity}$ ...5

Table 2 presents a convolutional neural network cluster calculation with a CNN accuracy rate of 0.98 percent for both left and right, and Table 3 displays the breast density type classification achievement with a 0.98% accuracy rate utilizing the ResNet152V2 method.

Table 2 CNN's performance in classifying breast cancer on the right and left.

Method	Sensitivity	Precision	Specificity	F-score	Accuracy
Right	0.897	0.976	0.966	0.869	0.943
Left	0.486	0.987	0.976	0.923	0.946

Table 3 ResNet152V2's breast concentration type classification effectiveness.

Method		Sensitivity	Precision	Specificity	F- score	Accuracy
Type A	**AV (Normal)**	0.869	0.976	0.746	0.786	0.861
	Normal	0.986	0.925	0.841	0.895	0.648
Type B	**AV (Normal)**	1.005	0.881	0.848	0.991	0.864
	Normal	0.983	0.976	0.96	0.964	0.897
Type C	**AV (Normal)**	1.008	0.977	0.89	0.879	0.971
	Normal	0.793	0.890	0.845	0.864	0.902
Type D	AV (Normal)	0.974	0.879	0.867	0.936	1.000
	Normal	1.000	0.934	0.836	0.834	0.812

Table 4 Efficiency of the mask R-CNN for classifying breast cancer cases.

Normal	Sensitivity	Precision	Specificity	F- score	Accuracy
Malignant	0.469	0.971	0.964	0.971	0.964
Benign	0.897	0.976	0.986	0.976	0.968

After that, Table 4 shows how well Mask R-CNN detects breast cancer, with an accuracy rate of 0.97%.
The diagram for the accuracy measure, which compares the testing and training accuracy values obtained throughout the training phase, is shown in Figure 6. With a rising most extreme level for preparing precision — which for ResNet152V2 was just achieved after 40 ages — Figure 7 exhibits how both exactness bends rise steadily as preparing goes on. Following 70 ages, [28], the train and approval precision levels changed somewhere in the range of 98% and 99.8%, with a typical testing dependability of 97.5% of the general testing exactness detailed.

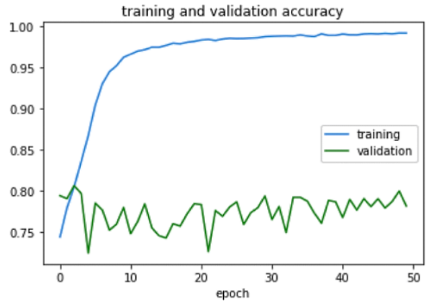

Fig. 6 Accuracy of training and validation vs epoch count (cnn).

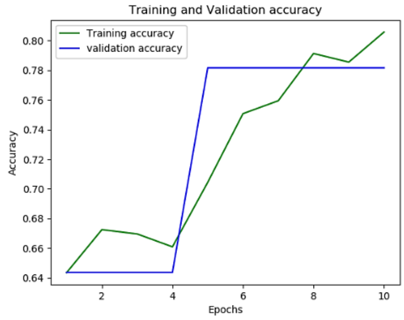

Fig. 7 Accuracy of training and validation vs epoch count (resnet152v2).

Table 5 displays the proportion to every kind of breast image in the test, verification, and training sets. In all, 414 images were included in the initial training set, [29], 43 in the validation set, and 43 in the experimental set.

Table 5 Distribution of all breast picture types in the test, validation, and training sets.

	Type A	**Type B**	**Type C**	**Type D**
Training	120	103	111	84
Validation	10	10	11	12
Test	10	10	11	12

Comparison of the outcomes of algorithms for detecting breast cancer in mammography using data gathered from an Erbil hospital. Physician data is used in the study with the assistance of radiologists and has a high degree of accuracy when all medical 1829 imaging data is on the chosen participants. Every mammography might show signs of breast cancer, although the locations, types, and shapes of the lesions differ. All samples were split into education and training, test, and validating sets using random selection. An analysis of the models employing the Mask R-CNN and the used methods. Evaluates the proposed study in comparison with reported past research [30]. A comparative research has been conducted based on the DL model's usage of multiple approaches, breast type density comparison, total number of cases included for the study, the model's accuracy, and coefficients.

VI. CONCLUSION

To the best of our knowledge, this work offers the first thorough assessment of four widely-used pretrained deep models, a suggested three-layered CNN architecture, gradient-based optimizers, and optimization hyper parameters for static ISL recognition. This study provided an exhaustive technique for the most precise mammography-based breast cancer being diagnosed. The following layout delineates the three phases of the research methodology. 99.3% was the result of comparing the right or left breast in the first phase using CNN. The four distinct types of breasts were analysed using ResNet152V2 in the subsequent phase, and the findings were 100% for both malignant and conventional cancers of the breasts. In the third stage, if the breast cancer was aberrant, the Mask R-CNN was used for comparing the malignant and benign cases; the accuracy of this comparison was 98%. Another study employed Mask R-CNN to estimate the size of the cancer.

FUTURE WORK

As technology develops further, these improvements to the algorithm may be used to other cancer instances such as lung cancer, presenting a considerably more comprehensive method for identifying and removing cancerous cells in the discovered region.

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