SEED GERMINATION PREDICTION USING CNN MODEL

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ABSTRACT

India is second only to China in global output of rice, wheat, sugarcane, cotton, groundnuts, and fruits and vegetables. Furthermore, it contributed 25% of the world's pulses over the past decade and will continue to do so through 2019. About 58% of India's population relies on agriculture for their income. In southern India, where 90 percent of the population lives, rice is the staple food for nearly all of its residents. Here The greatest difficulty in agriculture is increasing output per acre of land. In southern India, rice is a staple food. As a result of widespread use, there is a sizable demand for rice and rice-based products.

There are two main projects in our research: First, being able to recognise the various types Measure the potential for rice seeds to germinate. Our studies focus on four major types of rice that are grown by farmers in Tamil Nadu: 1) Andhra Ponni, 2) Pusa Ponni, 3) Vellari, and 4) Ponni. 2. AtchayaPonni Tiruchirappalli, Tamil Nadu, India is the source for both KO50 and IR20, which were obtained from the Tamil Nadu Agricultural University. Three colour features, thirteen morphological features, and eight textural features are extracted for a total of twenty-four. In this study, we propose a system to predict whether or not a rice seed will germinate by using previously trained convolutional neural network models. The proposed system's main goal is to equip any person with the ability to engage in agriculture through the use of a computer vision system. It's useful for picking out seeds. To put it another way, it boosts efficiency. In addition, it gives those who want to start farming but lack the necessary experience a place to do so. This study provided a straightforward and cost-effective method for estimating the likelihood that four distinct types of rice seed—AtchayaPonni, AndhraPonni, KO50, and IR20—will germinate. Applying CNN with pre-trained models like Alexnet, Resnet, and inception v3.0 prediction, we obtained 89%, 83%, and 98.44% accuracy, respectively, in our experimental analysis.

Keywords : CNN, Seed germinate, Computer vision, image processing.

1. INTRODUCTION

India's major exports include rice, wheat, sugarcane, cotton, groundnuts, and various fruits and vegetables. Furthermore, it contributed 25% of the world's pulses in the last decade,

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with production expected to continue at that rate through 2019. About 58% of Indians make their living in the agricultural sector. Rice is a staple food in India, providing sustenance for 90% of the southern population. Increasing agricultural productivity per acre of land is the most pressing issue in the agricultural sector. Since almost all arable land is already in use, rising productivity per acre of land is the key to feeding the world's growing population. In addition, water is in short supply, making agriculture an increasingly expensive commodity due to rising demands from industry and cities. Productivity can be increased by taking advantage of methods that increase yields, encourage diversification into higher-value crops, and build value chains to reduce marketing expenses [1].

Farmers are tending rice plants to meet rising demand, but the harvest is falling short of expectations. The results of a harvest can be affected by a wide variety of variables, such as the availability of water, the state of the weather, the presence or absence of insects, the presence or absence of certain plant species, the number of germinated seeds, the prevalence of disease, and the amount of fertiliser applied. New studies suggest that formation levels are directly proportional to the seeds chosen for formation. It is crucial to properly cultivate, manage, and harvest seed in order to maximise agricultural output and income. When starting with better quality seeds, harvests always improve [2-4].

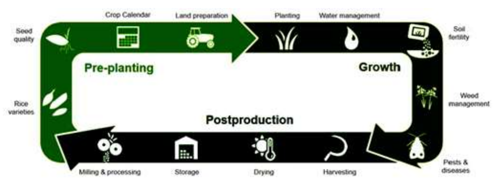

Fig.1. Productions That Happen in Steps

By far the most important step in the rice seed's life cycle is seed selection, as shown in Figure 1 from Rice Knowledge Bank's fundamental critical work (2020). There needs to be precision in the generation, harvesting, and processing stages for the highest possible yield and quality. The pre-planting process for rice includes selecting the right variety, making a cropping schedule, and preparing the field. Essential management decisions must be made during the growing phase of the rice crop. Considerations such as planting technique, water, fertiliser, weeds, pests, and diseases are all important. Post-harvest processes, such as drying, storing, and milling, are performed on rice paddy to improve its quality for human consumption and its commercial viability [5].

2. REVIEW LITERATURE

According to [6], this project aims to automate plant monitoring and smart gardening by means of the Arduino Mega Platform. The project's crowning achievement is its ability to diagnose the disease type via image processing. The steps of image processing include pre-processing, local feature extraction and segmentation, and classification. Methods are provided

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for four different diseases that can affect apple trees: those that cause unhealthy leaves, Black Rot, Rust, and Scab.

According to [7] The framework employs a variety of image processing techniques, including capturing, resizing, enhancing, segmenting, extracting regions of interest (ROIs), and extracting features from images. Images of pomegranate leaf diseases are used in the system's implementation. Experimental results show that the proposed framework can accurately identify damaged leaves from healthy leaves with a 98.39 percent success rate. In order to properly identify and classify pomegranate plant diseases, this paper aims to provide a diagnostic framework.

In order to distinguish cercospora from other types of spinach leaf disease, [8] propose using a Convolutional Neural Network (CNN) with the Resnet-50 architecture. With this method, you can identify and measure objects with a higher degree of precision using only a small number of training and testing datasets.

Using a combination of image processing and the Internet of Things (IoT), [9] propose a framework for on-tree fruit monitoring. In addition, the correlation coefficients between on-tree counting and off-tree counting and size estimation are 0.994 and 0.997, respectively.

According to [10], this technique helps farmers spot signs of infection on leaves even when they don't know what kind of pathogen is wreaking havoc on their crop. The method also decreases the amount of human intervention required to identify health problems.

Four image processing methods were presented by [12] for the real-time segmentation of cotton bolls in natural light. The chromatic aberration method had the highest recognition rate (91.05%), lowest false positive rate (6.41%), and highest false negative rate (4.88%) of all the proposed algorithms. The algorithm was evaluated at 81.31 and 97.53 percent, respectively, using the chromatic aberration technique.

This paper [13] uses geographic information technology to analyse climate problems in the agricultural production process, discusses agricultural resources' capacity to cope with sudden disasters, and proposes reasonable resource allocation suggestions to improve resource utilisation efficiency; all with the goal of effectively reducing the negative impact of climate change.

[14] The objective of this research is to develop a computer vision-based system capable of distinguishing between paddy types using a wide variety of criteria, including textural, external, and physical features. To deal with this problem, they created a T20-HOG (modified histogram oriented gradient) feature that can describe variations in paddy images' lighting, scale, and rotation. The results of their approach are shown in terms of four standard evaluation metrics, including accuracy (99.28 percent), precision (98.64 percent), recall (98.48 percent), and F 1 score (98.56 percent).

To do this, [15] developed an image processing method from a dataset of 375 images of paddy seed and extracted 20 key features (seven colour features, nine morphological features, and four texture features). Achieving accuracies of 83.8%, 93.9%, and 87.2% was accomplished by combining colour, morphological, and textural parameters. It was claimed

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that rice seed varieties could be categorised using the SVM-C method. We planted BR 11, BRRI dhan 28, and BRRI dhan 29 paddy seeds.

The seeds [16] were tested in a controlled environment after being subjected to drought stress during the plant's vegetative phase by decreasing the intensity of water delivery (63.5% moisture content). With a germination rate of 93.33 percent, the Inpara 8 variety rated higher than the Towuti variety (88 percent) in terms of seed quality. At the other end of the spectrum, the Inpago 8 variety had the slowest germination rate (2.71 days), lowest germination value (26%), lowest simultaneous growth (21.33%), and lowest vigour index (2.71).

According to [17], this new method can be used to get rid of duplicate varietals and check seed purity by correctly categorising seed types despite any physical similarities. There are a total of 158,421 OCT images in the dataset, and the proposed method has an accuracy of 89.6 percent when classifying these images, and 82.5 percent when classifying these images of Pokkali seeds. An OCT-obtained volumetric dataset was generated from (a) seven morphologically identical seeds of rice landrace Pokkali and (b) four rice varieties (PUSA Basmati 1, PUSA 1509, PUSA 44, and IR 64).

According to [18], Turkey cultivates five distinct varieties of rice: Arborio, Basmati, Ipsala, Jasmine, and Karacadag. There are 75,000 images in total, with 15,000 of each type of grain. There were calculations made to determine things like sensitivity, specificity, prediction, and accuracy. The Convolutional Neural Network (CNN) method was used for classification on the image dataset, while the Artificial Neural Network (ANN) and Deep Neural Network (DNN) algorithms were used to develop models for the feature dataset.

According to [19], two inexpensive devices were used for photographing the scene. The proposed method could be used in the seed industry, as well as in mobile apps for accurate and quick automated seed identification. In addition, the suggested vision-based model showed a high degree of reliability in identifying seed varieties, regardless of the camera used, the lighting conditions, or the imaging parameters.

In the case of [20],Some of the options include grayscale, resizing, edge enhancement, and histogram equalisation. K-Means clustering of rice image data. Recognizability was boosted by assigning different values to different colours and shapes. Above 95% recognition accuracy was achieved using test data consisting of 400 images of rice.

It is possible to generate more grain images from the same amount of data by employing image augmentation (rotation, brightness modification, and horizontal flipping), as described [21]. Findings show that both the CNN and bag-of-words models benefit from image augmentation. In the future, less data will be required for grain recognition.

In addition to spectral data, [22] present a feature set that significantly enhances classification results, highlighting the value of morphological and border-related characteristics. An openly available dataset of 8640 seed samples representing 90 different rice seed types was used to successfully evaluate the proposed method, with the average F1 score reaching 85.65% across 180 pairs of hyper spectral and RGB images.

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3. PROPOSED METHODOLOGY

Take a look at Figure 2 to see how the hardware for taking a test shot is arranged. Due to the low cost and widespread availability of black paper sheets, we opted to use those as the black background for the flatbed scanner.

Stores specialising in office supplies. To locate the sample, draw a square with a side length of 10 cm and put a dot in its centre. Put what kind of variety is being captured here on a small white piece of paper and tape it to the top of the page. As can be seen in the illustration above, there is a gap of 30cm between the mobile camera and the sample. That way, you get a clear image. This work also tested 40 cm, 20 cm, and 50 cm, and found that 30 cm provided the most comprehensive image. Here, we can see the proposed process laid out in Figure 3.

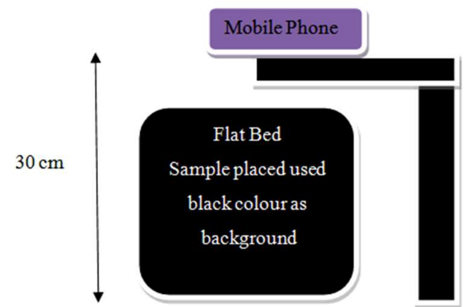

Fig.2. Setup of a Flat Bed Scanner

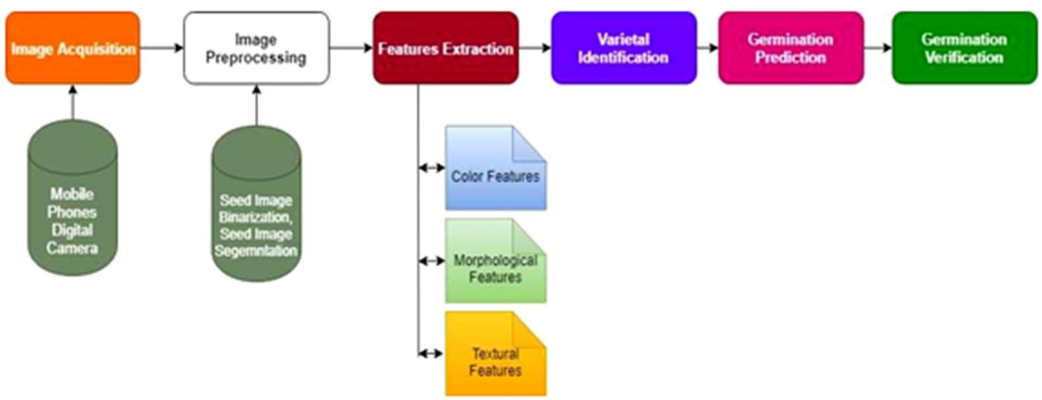

Fig.3. Process Flow Diagram

3.1. MATERIALS USED

The primary objective of this project is to implement a machine vision system for use in agricultural settings. Due to the labor-intensive nature of farming. Image processing techniques are widely used and implemented across many fields. As part of this research, we intend to present an automated method for predicting when rice seeds will germinate and for classifying different types of rice by their genetic makeup. The results of this study revealed the most practical approaches for achieving this goal without breaking the bank. These tools and methods were used to accomplish the task at hand.

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3.1.1.CAMERA

Now a days, nearly everyone has a smartphone equipped with a high-resolution camera. The image was taken with a 16-megapixel camera on a VIVO Z1 Pro Smartphone (approximately Rs. 15000/-).

In this case, the phone's camera takes fairly high-quality images with plenty of detail. Figure 4 displays the technical specifications of the mobile phone used in this study.

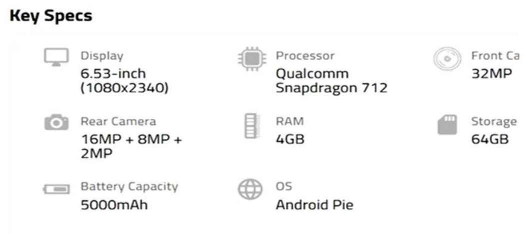

Fig.4. Vivo Z1pro Mobile's Specs

3.1.2. A COMPUTER AND RELATED MATERIALS

The collected images are stored and processed on an HP laptop equipped with a corei5 (8th Gen) processor, 4GB NVIDIA GEFORCE GTX, and a 1 TB HDD. The primary objective of this study is to find ways to simplify and reduce the expense of data set preparation. This work picked a black background for the flatbed scanner since black Price-wise, you can save a lot of money on colour sheets at the store. The wooden camera holder used here can be purchased at any local hardware store. The Philips Stellar Bright 20-Watt Round Light-Emitting Diode (LED) Bulb, which costs Rs.399/-, was utilised to illuminate the space and keep the temperature stable at 88 degrees.

3.2. IMAGE ACQUISITION

Multiple shooting modes are available on the mobile camera system. Our VIVO Z1 Pro Smartphone has a variety of shooting modes, such as Photo, AI Beauty, Night, PANO, PRO, and DOC. The authors of this work opted for PRO mode rather than another setting because the latter allows for the use of auto-adjustment software for a variety of image-related parameters. Yet, for image processing to work, it's essential that every shot be taken under identical lighting. Here, we decided to use PRO to correct the mode because we captured the same sample using different modes and got different results. Here, switch to PRO mode and set the camera's capturing settings to EV:-1.7 and ISO: 400. The room was kept at a constant temperature of 88 degrees and was lit with Philips Stellar Bright 20-Watt Round LED Bulbs.

3.3. IMAGING PREPROCESSING

Before extracting features from an image, the raw image has to be pre-processed. Segmentation, colour conversion, and image enhancement are all part of the pre-processing phase. Pre-processing techniques used in the actual research are described here.

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3.4. SEGMENTATION

The flatbed scanner's black background was created using sheets of black paper, which are cheap and widely available at office supply stores. Create a square that is 10 cm on a side. Place the sample in the middle of the square and label it. The image was cropped using Matlab's batch tool for image processing to create a 10cm by 10cm final product. Cropped images of the relevant varieties are shown in Figure 5 below.

3.5. CLASSIFICATION

It is necessary to first convert a colour image to grayscale, and then to black and white, in order to extract the features from the image. The Truecolor image as an m-by-n-by-3 numeric array. Grayscale images are returned as an m-by-n numeric array. Grayscale representations of GK50, BAP, GATP, and BKO50 are displayed in Figure 6.

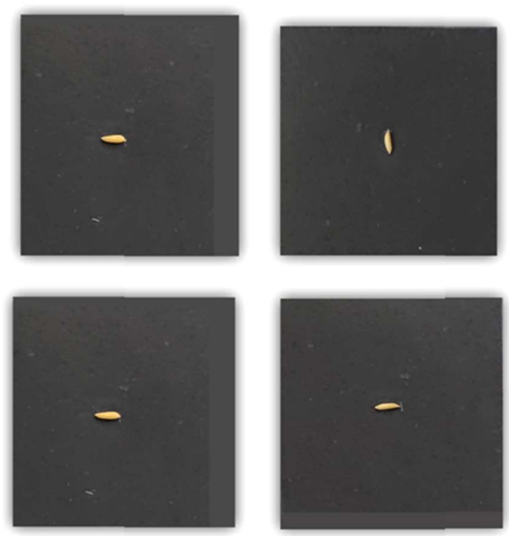

Fig.5. A cropped version of the GK50, GAP, GIR20, and GATP molecules.

This work sharpened the grayscale input image using the unsharp masking technique after the RGB images were converted to grayscale. The unsharp masking method borrows from a technique used to sharpen images for print by erasing a softer version of the original. One should not be confused by the name of this filter; an unsharp filter is actually a sharpening operator.

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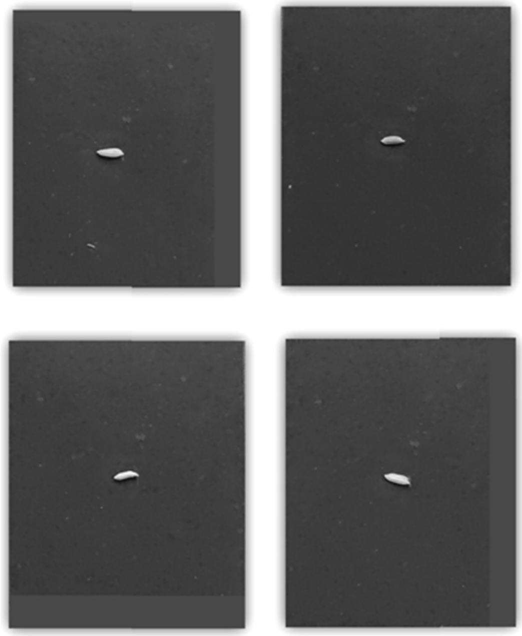

Fig.6. Grayscale image of GK50, BAP, GATP, and BKO50

A binary representation of the grayscale image is then created (Black and White image). In this study, a threshold-based adaptive method was used to convert an input image (I) into a binary output (BW). In adaptive mode, it uses the local first-order image statistics near each pixel to determine a locally adaptable image threshold. Local mean intensity (first-order) is used to set the cutoff.

Using the adaptthresh function, we can determine the local statistical order of each pixel's neighbours. Applying the threshold to the imbinarize function will transform a grayscale image into a binary one. If the image has Infs or NaNs, it is unclear how imbinarize will behave when using the "adaptive" technique. Perhaps Infs and NaNs spread beyond the immediate vicinity of Inf and NaN pixels.

Even if the sampled image is high quality, the input image will always have some dust or other imperfections. By using the bwareaopen(BWP) function, which removes all connected components (objects) from the binary image Black and White (BW) with fewer than P pixels, this work successfully filtered out the insignificant details. This method is commonly referred to as a "area opening." In this study, the same-shaped n-dimensional (N-D) convolution function was used to obtain a convolution whose centre component was the same size as BW2. Figure 7 depicts the state of the binary image after all conversions have been made and before features are extracted.

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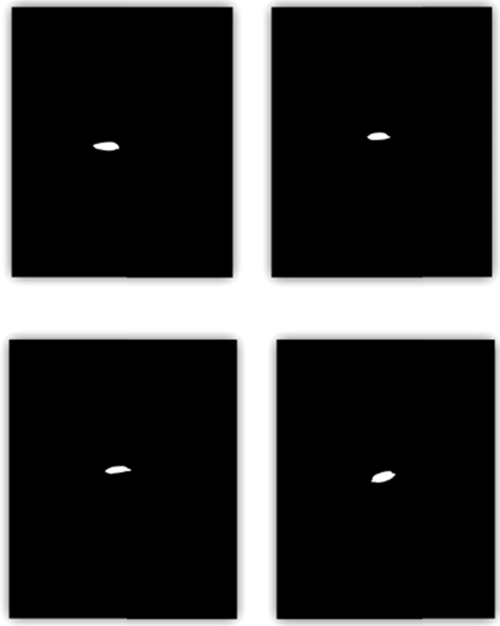

Fig.7. Images of GK50, BAP, GATP, and BIR20 in their binary forms

3.5.1. CHARACTERISTICS OF MORPHOLOGY

Elliptical-shaped image regions can be described by the following morphological characteristics.

- ✓Space
- ✓Primary Axis
- ✓Secondary Axis
- ✓Orientation
- ✓Eeccentricity
- ✓Equivalent Diameter
- ✓Perimeter
- ✓Solidity
- ✓Circularity

3.5.2. ASPECTS OF TEXTURE

In this study, GLCM is utilised to implement four texture characteristics: 1)contrast, 2)correlation, 3)entropy, and 4)homogeneity. The system's eight textural qualities are implemented using GLCM in both the horizontal and vertical directions. There are eight different texture properties, and they are as follows: 1) horizontal contrast, 2) horizontal correlation, 3) horizontal entropy, 4) homogeneity horizontal, 5) vertical contrast, 6) vertical correlation, 7) vertical entropy, and 8) vertical homogeneity.

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4. RESULT AND DISCUSSION

For the purposes of this study, we focused only on the seed's varietal purity and our ability to predict its germination rate. However, when machine learning algorithms were applied to both variables in this study, the resulting accuracy in varietal identification was greater than 92%. However, a prediction accuracy of 70% for germination is below what is desirable and expected. This work has used three different CNN pre-trained network models—Alexnet, Resnet, and inception v3.0 prediction—to improve germination prediction accuracy.

Good productivity can be attained through careful seed selection. Many people today lack the necessary expertise in seed and crop selection to begin farming. It causes a decrease in output. This study proposes a CNN-based germination prediction system for rice seeds as a solution to the problem. This research has provided a straightforward and cost-effective method for gauging the viability of four major rice varieties grown by farmers in Tamil Nadu: AtchayaPonni, AndhraPonni, KO50, and IR20. Using CNN with pre-trained models like Alexnet, Resnet, and inception v3.0 prediction, the authors of this work were able to achieve 89.83%, 83.33%, and 98.44% accuracy, respectively, in their experimental analysis.

This work has begun germination prediction by applying deep learning algorithms for classification once the germination results have been recorded. The captured images have been shown in the previous part of this work, and they have been cropped to a length of 450 and a width of 300 pixels Estimated height: 450. Figure 8 displays cropped images of the sampled varieties.

Fig.8. Cropped images of samples

4.1. MODEL OF ALEXNET CNN

It is common practise to resize images so that they are optimal for the respective CNN pretrained networks before applying deep learning algorithms. To compare, Resnet101 can

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handle images with a size of 224 by 224 pixels, while Inception V3 can handle images with a size of 299 by 299 pixels. During the training phase of AlexNet, this study used a total of 630 samples, from which 344 were successful.

To the tune of 286 from seeds that failed to germinate. A total of 270 samples were used for validation, including 148 germinated samples and 122 non-germinated samples that were fed into the trained network. The Alexnet model's training data is depicted in Figure 9, while validation data is depicted in Figure 10.

AlexNet is a convolutional neural network with eight layers. When using the ImageNet database, you can import a network that has already been trained on more than a million images. In its training, the network was instructed to divide images into over a thousand distinct classes. The network has amassed a large collection of detailed feature representations for many different types of images. The network can accept images up to 227 pixels wide and tall as input. This pre-trained model's fully connected layer is made up of 25 individual layers. Due to the fact that our input data was already split into two categories—germinated and non-germinated—this work modified the output classes to reflect that. In the training phase, this study used stochastic gradient descent with momentum (sgdm), with an initial rate of 0.0001, 200 epochs, and a batch size of 50. Figure 11 displays the results from training and validating the Alexnet model. An accuracy of 88.15 percent was found in the validation of this work. Sample size and AlexNet-generated accuracy are displayed in Tables 1, 2, and 3, respectively.

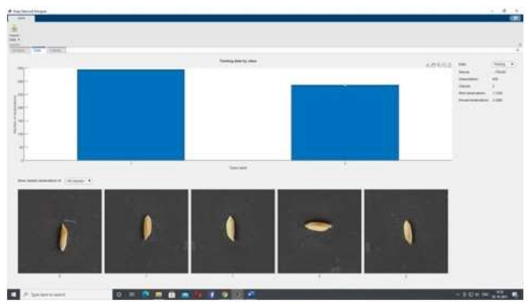

Fig. 9: AlexNet Training Data

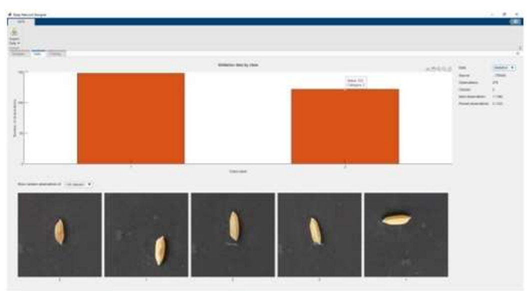

Fig.10. Validation Data for the AlexNet

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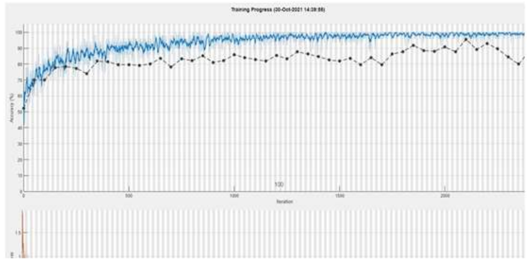

Fig.11: The AlexNet Validation Outcome

Table 1. Alexnet Accuracy and Sample Size Distribution

Phase	Category	Number of samples
Training	Germinated	344
	Non-Germinated	286
Validation	Germinated	148
	Non-Germinated	122
Epochs		200
Batch size		50
Accuracy		88.15%

Table 2. AlexNet Evaluation Results

Category	Germinated	Non-Germinated
Germinated (112)	99	13
Non-Germinated (88)	9	79

Table 3. The AlexNet Performance Metrics

Metric	Result in Percentage
Accuracy	89
Precision	88
Recall	92

4.2. MODEL OF RESNET 101

The ResNet-101 network has 101 hidden layers and is a deep convolutional neural network. For this work, a pre-trained version of the network can be accessed through the ImageNet database. This version has been trained on more than a million images. Images can be sorted into one thousand distinct categories by the network, including keyboards, mice, pencils, and many different kinds of animals. Thus, the network has picked up the ability to represent images with a wide range of rich features. Image sizes of 224 by 224 pixels are accepted by the network. As our data included both germinated and non-germinated items, we

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found it necessary to modify the output classes to reflect this. Stochastic gradient descent with momentum (sgdm) was employed in the training phase, with an initial rate of 0.0001, 100 epochs, and a batch size of 100. This piece of work was validated to have an accuracy of 78%. Tables 4, 5, and 6 detail the sample used and the accuracy achieved by applying the Resnet101 Model.

Table 4. Resnet101 Accuracy and Sample Size Distribution

Phase	Category	Number of samples
Training	Germinated	344
	Non-Germinated	286
Validation	Germinated	148
	Non-Germinated	122
Epochs		100
Batch size		100
Accuracy		78%

Table 5. Resnet101 Test Outcomes

Category	Germinated	Non-Germinated
Germinated (112)	100	12
Non-Germinated (88)	22	66

Table 6. Resnet101 Performance Metrics

Metric	Result in Percentage
Accuracy	83
Precision	89
Recall	82

4.3. MODEL V3 OF THE INCEPTION

48 deep convolutional layers make up Inception-v3. By accessing the ImageNet database, this work can make use of a network that has already been trained on more than a million images. One thousand distinct classes of objects can be identified by the network in any given set of image.

which includes animals as well as keyboards, mice, pencils, and other office supplies. Thus, the network has picked up the ability to represent images with a wide range of rich features. It takes pictures that are exactly 299 pixels square for the network to work properly. As our data included both germinated and non-germinated items, we found it necessary to modify the output classes to reflect this. This study employed Stochastic Gradient Descent with Momentum (SGDM) in the training phase, with an initial rate of 0.0001, 25 epochs, and a batch

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size of 100. The validation accuracy for this work was 98.4%. Tables 7, 8, and 9 detail the data set and the precision gained by employing the Inception V3 Model.

Table 7. Data Accuracy and Sample Sizes in Inception V3

Phase	Category	Number of samples
Training	Germinated	400
	Non-Germinated	320
Validation	Germinated	100
	Non-Germinated	80
Epochs		25
Batch size		100
Accuracy		98.4%

Table 8. Test Results for Inception V3

Category	Germinated	Non-Germinated
Germinated (112)	110	02
Non-Germinated (88)	02	86

Table 9: Inception V3's Performance Metrics

Metric	Result in Percentage
Accuracy	98
Precision	98
Recall	98

4.4. DISCUSSION

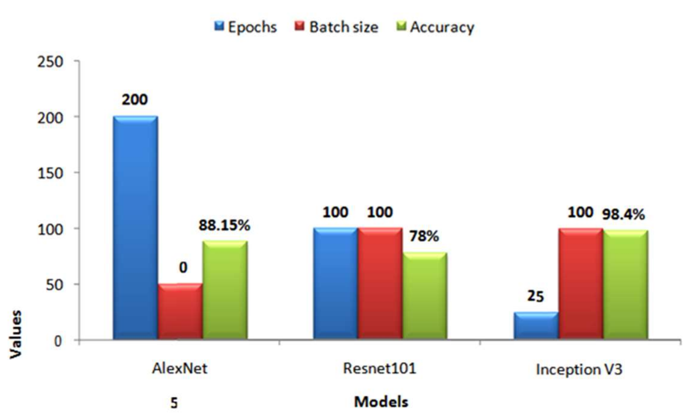

Fig.12. No of Samples used and Accuracy

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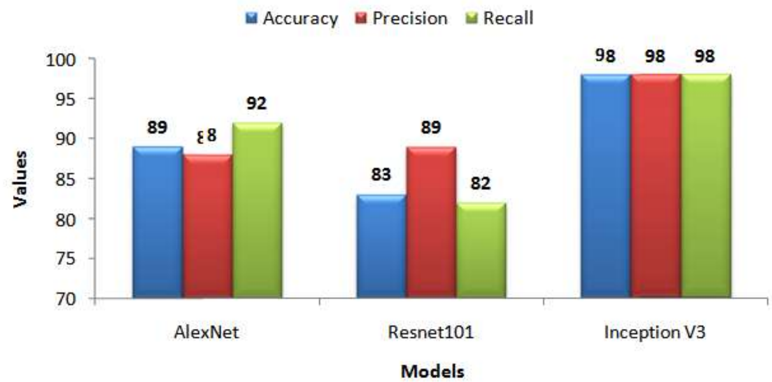

Fig.13.Comparison of model performance metrics

5. CONCLUSION

This part presents and briefly explains the machine learning algorithms used to predict germination based on features extracted from samples. The accuracy percentages generated by applying seventeen different classification algorithms are tabulated below. Predictions of germination with an accuracy of 70% are unacceptable and below expectations. The use of CNN pre-trained network models, such as Alexnet, was thus implemented to improve germination prediction accuracy.

Accuracy estimates from RESNET, INCEPTION v3.0 prediction, and were 89%, 83%, and 98.44%, respectively. Several quality factors for comparing algorithms were discussed, as were the sizes of the training, validation, and test datasets used.

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