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On the Raw Cotton Image Classification Model using Convolution Neural Network Architecture

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Abstract: Suicides in general, including farmers' suicides, are a sad and complex phenomenon. Hence, their underlying causes need to be addressed within an equally complex societal framework. Although officially recognized for having increased production and farmers' income, through cotton farming, genetically-modified, insect-resistant cotton, remains highly controversial in India. Among other allegations, Defective sorting of cotton crop in the market and thereafter raw cotton classified in to different Grades based on which rates are determined, After selling the cotton in the local market, wrong Grading of the farmer's crop ,leading him in financial trouble is also the cause of farmer's suicide. In this paper, we provide a worth Cotton Grading solution on cotton and farmer suicides, taking into account information from published official and unofficial reports, peer-reviewed journal articles ,we first gather the 9171 raw images of fresh raw cotton and cotton yarn samples directly from the farm field. Second, we manually classified the collected samples in three different categories. Cotton classification using ANN was experimented which has generated disappointing results initially in some particular categories and further proposed technique of CNN has provided improvement in accuracy and minimum Sparse categorical Entropy. At the end we concluded the paper by proposing a conceptual framework for empirical applications linking the different agricultural and institutional factors that could have contributed to farmer suicides in recent years in certain districts of Central and Southern India.

Index Terms **- Accuracy, Deep learning, CNN, Log loss, Prediction.**

I. INTRODUCTION

Farmer suicides in India remain a deeply distressing and multifaceted issue that reflects the broader socio-economic and structural challenges facing rural agricultural communities. Among the many crops cultivated across the Indian subcontinent, cotton stands out not only for its economic importance but also for its association with some of the most alarming rates of distress among farmers. While genetically modified (GM) cotton, particularly the BT cotton variant has been officially recognized for increasing yields and improving income levels, it has also sparked significant controversy and debate. Critics have pointed to several unintended consequences, including rising input costs, pest resistance, and most notably, systemic issues in post-harvest grading and marketing practices. One such systemic issue arises from the defective grading of raw cotton in local markets. Cotton brought to market is typically sorted into quality grades, which directly determine the price offered to farmers. However, inconsistencies, lack of transparency, and manual errors in this grading process often result in misclassification of cotton quality. When high-quality cotton is incorrectly graded as lower quality, it leads to financial losses for farmers who have already invested heavily in production. For many small and marginal farmers, this financial strain becomes a tipping point, pushing them into unmanageable debt and, tragically, in some cases, leading to suicide. These market-level failures are rarely addressed with the urgency they require, despite their devastating human impact.

To address this critical gap, the present study proposes a technological intervention, an image classification framework using deep learning techniques to automate and standardize the cotton grading process. This work is grounded in the hypothesis that consistent, unbiased, and efficient grading of raw cotton can significantly reduce one of the hidden stressors contributing to agrarian distress. We first created a comprehensive dataset consisting of 4,000 raw cotton and cotton yarn images captured directly from farm fields under real-world conditions. These samples were manually annotated into three categories based on quality i.e. Grade 1, Grade 2, and Grade 3, ensuring domain relevance and annotation reliability. In the initial phase of experimentation, we applied an Artificial Neural Network (ANN) to the dataset. While this traditional machine learning approach demonstrated some promise, it yielded suboptimal performance in certain categories, particularly where the visual differences between grades were subtle. Consequently, we advanced our methodology by implementing a Convolutional Neural Network (CNN) architecture, specifically tailored for image classification tasks. The CNN model demonstrated significant improvements in classification accuracy and reduction in sparse categorical cross-entropy, establishing its superiority over earlier methods in handling high-dimensional visual features typical of cotton fibers.

This research thus not only contributes to the technical domain of agricultural image classification but also addresses a critical social challenge. By offering a reliable framework for automated cotton grading, the model holds potential to mitigate the economic

injustices experienced by farmers during crop marketing. Ultimately, the paper concludes by proposing a conceptual framework for empirical and policy applications that link technological interventions to broader agricultural and institutional reforms. This framework may be particularly relevant to agrarian regions in central and southern India, where farmer suicides remain a persistent and tragic concern.

II. REVIEW OF LITERATURE

Patrícia Dias Araújo et al. (2017) presented a steps model classification in the cotton oil semi-refining process by image processing. Two algorithms with different recognition patterns were analyzed: K-Nearest Neighbor and Quadratic Discriminate Analysis, with a validation strategy Leave-one-out and the neural network Extreme Learning Machine using Fold validation technique. Both algorithms reached success rates of more than 90%, and the best result was obtained through the applied neural network, with more than 95% of accuracy. Data has been saved on file for further analysis, thus avoiding human interaction. Therefore, the results obtained in the classification were satisfactory, thus fulfilling the initial objective of the article.

D. A. Bhagya M Pati et al. (2017) has presented the article on the leaf segmentation of different plant such as Jackfruit, Banaba, Cotton and etc. Experiment have been carried out using greedy snake algorithm and it is compared with the M Kass snake algorithm The proposed algorithm has been applied to the database of more than 80 images of different leaves of different species tree of 224 by size depending on the aspect ratio. The results of the proposed algorithm are compared with the M Kass snake model. From the results, it is concluded that greedy algorithm is faster and efficient.

Adhao Asmita Sarangdhar (2017) this paper presents a system for detection and controlling of diseases on cotton leaf along with soil quality monitoring. The work proposes a Support Vector Machine based regression system for identification and classification of five cotton leaf diseases i.e. Bacterial Blight, Alternaria, Gray Mildew, Cereospra, and Fusarium wilt. After disease detection, the name of a disease with its remedies will be provided to the farmers using android app. Vision sensors for soil quality monitoring are interfaced using Raspberry Pi which make it independent and cost effective system. The overall classification accuracy of this proposed system is 83.26%. The present system gives promising results for disease detection and proves its effectiveness to the farmers to improve the crop production.

Toan Bui et al. (2017) has presented an automatic segmentation method used to detect cotton wool spots in the retinal images for diabetic retinopathy disease. A neural network model is employed for learning task and tested by k-fold cross validation. In proposed work, color features such as RGB space, intensity and the texture features as contrast, range, mean, and entropy are extracted. An algorithm is evaluated by ground truth on DIARETDB1 public data. The result shows that cotton wool can be segmented by this method with 85.9% in sensitivity, 84.4% in specificity, and 85.54% in accuracy.

Jayraj Chopda et al.(2018) presented state of the art farming technique that offers high ended application of modern farming by acquiring multiple data from sensors, robots, live stream and social media. In the present article author would like to propose a system which can predict cotton crop diseases using 'Decision Tree Classifier' by taking parameters as temperature, soil moisture, etc. The proposed system can predict the cotton crop diseases using decision tree with the help of the parameters like temperature, soil moisture, etc. based on the previous year data and through sensors. The future scope of the project would be focusing on building an Android Application.

Syna Sreng et.al.(2018) highlighted that little work done on detection of cotton wool spots, mainly because of the fact that its appearances are difficult to filter out from the background and not clearly visible. In his article, an algorithm is proposed to detect cotton wool spots based on integrating Principal Components Analysis and Support Vector Machine. The adaptive thresholding method is used to roughly extract the cotton wool spot from the background. The proposed method was evaluated with local and DIARETDB1 datasets containing 289 images. Given a success rate of accuracy 90.47 %, sensitivity 85.29%, and specificity 90.12% with the average computational time 16.47 seconds per image on cotton wool spots detection, , the results showed that the proposed system performed better by comparing to the previous research works.

Yueyue Cai et al.(2019) proposed a novel classification method of trash types in cotton using depth-wise separable convolutions using deep neural networks. The experiment results show that this method can improve the classification accuracy of trash types in cotton. In present article, author uses the classification recognition model of deep neural network Vgg16 to classify cotton trash types. The total classification accuracy of test datasets is as high as 90.62%. In order to further improve the accuracy of the classification, the parameters of the deep neural network still need to be improved.

A. Jenifa et.al.(2019) has introduce Deep Convolutional Neural Network based approach for identifying Cotton leaf diseases automatically. In proposed work, Deep CNN is used to detect cotton leaf disease. He train our data and assess the experimental result which shows the average accuracy of 96 %. Author detected the cotton leaf disease, our method evaluate up to 96% accuracy for classification of diseased cotton leaves like, Cercospora, Bacterial blight, Ascochyta blight, Target spot images on MATLAB.

X. Z. CHAO NI(2020) This paper presents a novel sorting algorithm for the online detection of film on cotton using hyperspectral imaging with a spectral region of 1000 - 2500 nm. The sorting algorithm consists of a group of stacked auto encoders (SAE), two optimization modules and an extreme learning machine (ELM) classifier. A group of experiments was carried out to evaluate the performance of the proposed sorting algorithm using cotton that was provided by a Xinjiang municipality cotton ginning company. The experimental results show that the VW-SAE can improve the classification accuracies by approximately 15 %. The overall recognition rate of the proposed algorithm is over 95.58 %, and its recognition time is comparable to some state-of-the-art methods the proposed algorithm has a good application prospect and the similar idea can be applied into other fields, such as wheat and stalk separations.

Wajeeha Shakeel et.al.(*2020)* has demonstrated cotton disease detection by using image processing techniques. Cercospora Leaf Spot (CLS) is a severe problem that may decline cotton production. About 80-95% of the diseases in cotton leaves are similar to

Alternaria, Erythema, Leukoplakia, and Macula on leaves. The K-means clustering algorithm is used for the segmentation of image into clusters. The extraction of features is done by using the hybrid method for texture and color feature extraction. Finally, Support Vector Machine (SVM) is used for the classification of Cercospora cotton leaves. At the end, precision and recall performance evaluation metrics are used to evaluate the accuracy and it is found that about 96% accuracy is achieved.

O. K. Pal (2021) presented this article to identify paddy leaf diseases. The proposed scheme is built using CNN with a pre-trained ResNet-50, ResNet-101, VGG-16, VGG19, EfficientNet, Inspection-V2, and GoogleNet library. A ReLU classifier is used to enhance the accuracy and efficiency of the identification process. The system's highest average accuracy for all five identifications is 96.27% for the ResNet-50 pre-trained library, and the F1 Score is 98.19%. The accuracy can be maximized by expanding the dataset. A detection system based on Convolutional Neural Networks is capable of detecting paddy leaf conditions. This system can classify paddy leaf disease within a short time along at a low cost.

Zekai Feng et.al (2021) proposed an object detection algorithm based on Faster-RCNN to identify the stage of the cotton leaf (a period that cotton leaves grow). The algorithm consists of three main parts: convolutional neural network based on ResNet101, the extraction of candidate regions of the target based on RPNs, and the identification of detection object. Based on many experiments, the algorithm in this article become able to identify the cotton leaf stage, and the precision surpasses 80%. Through many experiments, the algorithm in proposed work can realize the identification of the cotton leaf stage, and the accuracy is more than 80%. It's highlighted that author thoroughly analyzed the essence of region proposal networks and data processing. Accordingly and designed their region proposal network and data processing. As a result, the experiments employing the algorithm has demonstrated promising results, which convince us that our solution is adaptable in practice.

Ananda S. Paymode et.al.(*2021)* has intensify the proposed research work on detecting and classifying the accurate type of diseases occurred on leaf at early stage. Principle objective of present work is to address the problem using the Deep Learning (DL) techniques. There are total six types of crops leaf images (tomato, grapes, soybean, sugarcane, cotton and onion) collected. The tomato diseased leaf selected for detection and classification. The CNN based model gave the highest accuracy of 97 % which is highest forever for real captured diseased images In our research paper, total six types of crops leaf images collected and prepared the dataset for tomato leafs. With use of data augmentation techniques, evaluation metrics parameter accuracy increased as compared to others available datasets.

Sathishkumar Samiappan et.al. (2021 has found, southern root-knot nematode (RKN), a soil borne roundworm, threatens cotton and other crops. In present work, author study the effect of RKN on leaf reflectance using a spectrometer under controlled-environmental conditions. The authors has applied statistical supervised learning algorithms to classify RKN infected cotton from the control group. Author has tried to find an accuracy by selecting the visible and near infrared spectra (350-2500nm) and partial spectra (350- 1000nm) as a supervised classifier data set. Author also investigates temporal misalignments between training and testing conditions. The presented results show the possibility of using hyperspectral data to detect RKN infection in cotton. Machine Learning classifier produced very good accuracies in classifying healthy cotton plants from the nematode infected plants. Authors also promise that, plant traits and soil microbiome compositions will be compared with hyperspectral data to develop robust proxies (spectral bands) to detect the early-stage root-knot nematode infection.

Xifeng Ju et.al.(2021) has found, Xinjiang produce more than 80% of China's cotton production, accounting for nearly one quarter of global cotton production. Therefore, crop growth monitoring, disaster warning, disaster assessment and post-disaster recovery work is very important. Based on Google Earth Engine remote sensing big data cloud computing platform and high spatial and temporal resolution remote sensing image data Sentinel-2 was used to study the Kuitun Reclamation Area of the Seventh Division of Xinjiang Production and Construction Corps, a typical cotton growing area in Xinjiang. The time series remote sensing data, the cotton change patterns and key temporal phase data of cotton in different months were extracted by the time series analysis method, and combined with the unique spectral information and texture features of cotton. The accuracy of cotton planting area and planting range extraction based on remote sensing images was verified, and the overall classification accuracy was above 90%, According to the verification, its classification accuracy is more than 90%, which can meet the application requirements of cotton growth monitoring and evaluation in this region. The following conclusions are drawn: Author has also finds, Google Earth Engine based on remote sensing big data cloud computing has strong advantages in all aspects, such as the processing efficiency and the amount of data processed.

III. DATA COLLECTION

Colour grade is determined by the degree of reflectance (Rd) and yellowness (+b) as established by official standards and measured by the high volume instrument. Reflectance indicates how bright or dull a sample is, and yellowness indicates the degree of pigmentation. A three-digit colour code is determined by locating the point at which the Rd and +b values intersect on the colour chart for American Upland cotton (shown on The colour of cotton fibres can be affected by rainfall, freezes, insects, fungi, and staining through contact with soil, grass, or cotton plant leaf. Colour can also be affected by excessive moisture and temperature levels during storage, both before and after ginning. Colour deterioration because of environmental conditions affects the fibres' ability to absorb and hold dyes and finishes and is likely to reduce processing efficiency. Trash is a measure of the amount of non-lint materials in cotton, such as leaf and bark from the cotton plant. The surface of the cotton sample is scanned by a digital camera, and the digital image is analysed. The percentage of the surface area occupied by trash particles (percent area) and the number of trash particles visible (particle count) are calculated and reported. The ratio between percent area of trash and trash particle count is a good indicator of the average particle size in a cotton sample. For instance, a low percent area combined with a high particle count indicates a smaller average particle size than does a high percent area with a low particle count. A high percent area of trash results in greater textile mill processing waste and lower yarn quality. Small trash particles, or "pepper trash," are highly undesirable, because they are more difficult for the mill to remove from the cotton lint than are larger trash particles.The conventional method of "grading the cotton crop" has become obsolete, that is why urgent attention required to pay towards reliable classification solution from research community and fortification strategy makers. In recent year, computer-aided image classification from raw cotton

wool images can be a beneficial measure. Nevertheless, so far, such datasets are not available. Hence, the "Raw Cotton Wool Image Dataset (RCWID)" is created by collecting and processing sample images from different parts of the farm field i.e., from farm fields, yarns, Cotton Ginning & Pressing Industries and publicly accessible case reports.

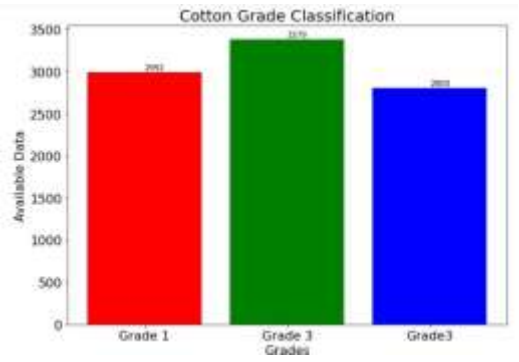

Figure 1 Raw cotton image data distribution

The creation of "Raw Cotton Wool Image Dataset" is primarily focused on distinguishing the Pure White fresh Cotton cases from the similar contaminated cases. Therefore, along with the 'Grade 1' class, we included contaminated images of "Yellow colored old cotton" and 'Trash mixed cotton" because of their resemblance to the cotton wool and yarn cotton in initial state in another class named 'Others Grade' to perform multiclass classification. There are 3 folders in the dataset. Original Images: It contains a total number of 9171 images, among which 2992 belongs to the ' Pure White fresh Cotton ' class and the remaining 6179 samples represents the Contaminated cases **i.e.,** Yellow colored old cotton and 'Trash mixed cotton **cases.** Augmented Images: To aid the classification task, several data augmentation methods such as RandomRotation, RandomZoom, RandomFlip, etc. have been applied using Keras which is the high-level API of TensorFlow library in Python 3.9.12. Although this can be readily done using ImageGenerator / experimental. Preprocessing image augmenters, to ensure reproducibility of the results, the augmented images are provided in this folder. Post-augmentation, the number of images increased by approximately 10 folds. The total classes of sample images have 687,779 parameters. To avoid any sort of bias in training, three-fold cross validation was performed. The original images were split into training, validation and test set(s) with the approximate proportion of 80: 10: 10 while maintaining classification reliability. According to the commonly perceived data preparation practice, only the training and validation images were augmented while the test set contained only the original images.

Figure 2 Random Cotton images for Training and Testing

IV. EXPERIMENTAL SETUP

A Convolutional Neural Network (CNN) is a Deep Learning Neural Network mostly used for images which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a CNN is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, CNN have the ability to learn these filter characteristics.

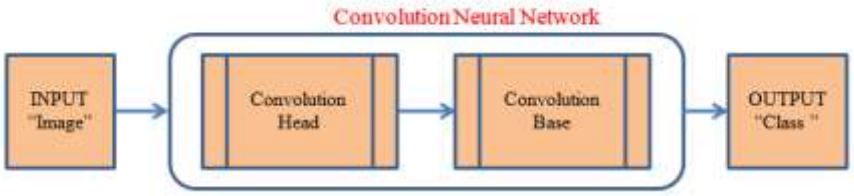

Figure 3 Convolution Neural Network

In a proposed research work, an attempt is made to solve, image classification problem by using transfer learning technique through deep learning approach. Convolution Head is designed with three feature maps , each consisting two dimensional convolution layer followed by Max pooling layer (could include layers like Dropout layers (regularization), Padding layers, etc.) to extract the most prominent features of the raw image. The Convolution Base is used to classify the image by passing the sample images through the Convolutional layer using Flattening Layers and Passed on to the Fully Connected Dense Layer which deals with an array of values. The last layer will typically be a Dense Layer with sigmoid or softmax function (multiclass classification) with the output size = three classes (i.e. “Grade 1”,”Grade 2”,”Grade 3”)

V. PRFORMANCE METRICES

A confusion matrix is a fundamental tool in evaluating the performance of classification models. It summarizes how well a model predicts the actual labels, allowing us to quantify errors and successes in classification. Essentially, it is a table with four key outcomes for binary classification: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). These outcomes form the basis for several important metrics: accuracy, precision, recall, and F1-score.Accuracy measures the proportion of correctly classified instances among all predictions. It reflects how often the classifier is correct overall and is computed as the sum of true positives and true negatives divided by the total number of samples. While accuracy provides a general sense of performance, it can be misleading in imbalanced datasets. For example, if 95% of the samples belong to one class, predicting all samples as that class yields high accuracy but poor real-world performance. Precision focuses on the quality of positive predictions. It quantifies the proportion of correctly identified positive instances among all instances predicted as positive. High precision indicates that the model rarely mislabels negative instances as positive. Recall, also called sensitivity or true positive rate, assesses the model’s ability to detect actual positive cases. It measures the proportion of actual positives that are correctly identified. High recall means the model successfully captures most positive instances. Finally, the F1-score provides a balanced measure by combining precision and recall into a single metric. It is the harmonic mean of precision and recall, which penalizes extreme disparities between the two. F1-score is particularly useful when one needs to consider both false positives and false negatives:

Table 1 Performance metrics of the proposed CNN

$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$	$Precision = \frac{TP}{TP + FP}$
$Recall = \frac{TP}{TP + FN}$	$F1 - Score = \frac{2(Precision * Recall)}{(Precision * Recall)}$

VI. RESULTS AND DISCUSSION

The confusion matrix depicted in the figure provides a clear and insightful evaluation of the performance of the proposed convolutional neural network (CNN) model. The model attempts to classify raw cotton images into three quality grades: Grade 1, Grade 2, and Grade 3.The matrix layout follows a typical format where rows represent the actual (true) classes of the cotton samples, and columns represent the predicted classes produced by the model. Each cell in the matrix indicates the number of samples corresponding to a specific true-predicted class combination. Diagonal values represent correct predictions, while off-diagonal values correspond to misclassifications. For Grade 1 (class 0) cotton samples, the model has achieved perfect classification accuracy. All 20 images that truly belong to Grade 1 were correctly identified as such, with zero misclassifications. This outcome indicates that the model has successfully learned the distinguishing features of high-quality cotton, possibly due to clearly defined visual attributes such as fiber brightness, cleanliness, or uniformity. In the case of Grade 2 (class 1) cotton, the model correctly classified 15 images but misclassified 3 of them as Grade 3. This implies a moderate level of confusion between Grade 2 and Grade 3 cotton, which could be attributed to overlapping visual textures or color similarities in the raw images. Additionally, one image from Grade 3 was wrongly predicted as Grade 2, suggesting that these two classes share subtle characteristics that challenge the discriminative ability of the CNN in certain scenarios. For Grade 3 (class 2) cotton, the model performed well, with 21 correct predictions out of 22 samples. One image was incorrectly predicted as Grade 2, again reinforcing the possibility of visual overlap

between mid-quality and low-quality cotton images. Nevertheless, the high number of correct predictions shows that the model can reliably detect patterns and features associated with lower-grade cotton.

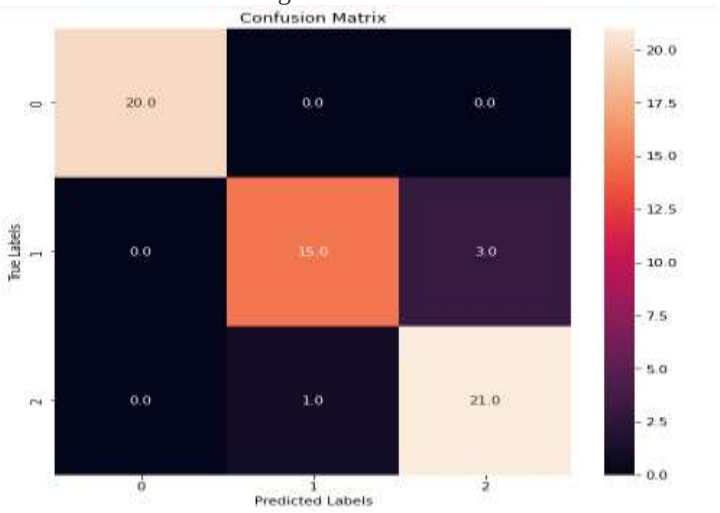

Figure 4 Confusion matrix of validated CNN model

The proposed model demonstrates a high classification accuracy of 83.33%, derived from 56 correct predictions out of 60 total samples. The precision and recall scores are strong across all three classes, with Grade 1 showing perfect precision and recall, and the other two classes also exhibiting values above 85%, as inferred from the minimal misclassifications. The F1-scores, which combine precision and recall into a single metric, further affirm the model's balanced performance.

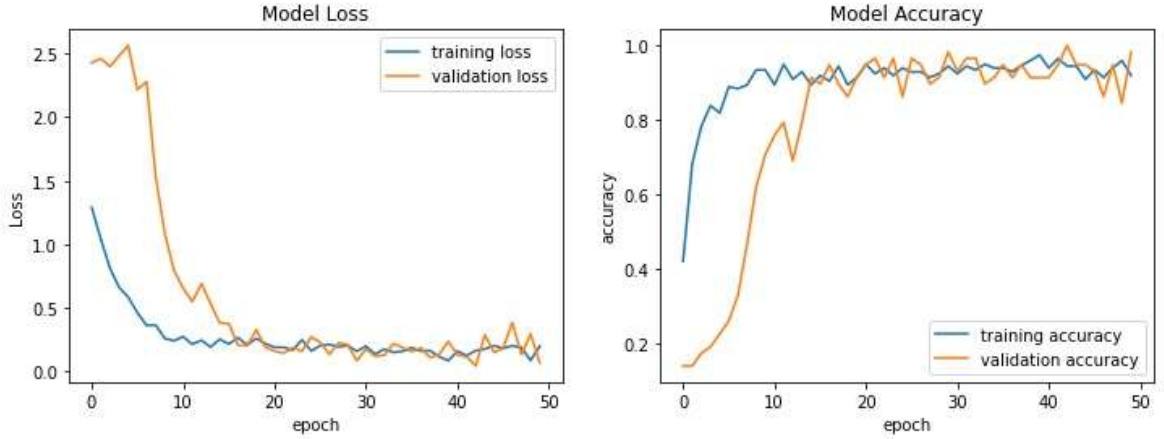

Figure 5 Graphical representation of real time evaluation of CNN

The training performance of the proposed Convolutional Neural Network (CNN) architecture is effectively captured through the pair of plots displaying model loss and model accuracy over 50 epochs. In the model loss plot, we observe that both the training and validation loss begin at relatively high values in the early epochs. The training loss starts to decline rapidly within the first 10 epochs, suggesting that the model quickly learns to extract meaningful features from the cotton images. The validation loss, although initially more erratic, follows a similar downward trend and stabilizes around epoch 20. Beyond this point, both losses converge and continue to maintain low values, with only minor fluctuations observed in the validation curve. This convergence indicates that the model is not only fitting the training data well but is also generalizing effectively to unseen data. Therefore, the loss behavior affirms that the CNN model is stable and well-regularized. The model accuracy plot complements this analysis by illustrating how classification accuracy improves throughout training. Initially, the training accuracy rises steeply, reaching values close to 95% by the 10th epoch. Validation accuracy starts much lower but rapidly increases and nearly matches the training accuracy around epoch 15. From that point onward, both accuracy curves remain high and consistent, hovering between 90% and 100%. This high level of accuracy on both datasets confirms that the model has successfully learned to differentiate between the cotton grades with high reliability. The graphical performance clearly demonstrates that the CNN model designed for classifying raw cotton images is both efficient and robust.

Table 2 Results of Descriptive Statistics of Study Variables

	precision	recall	f1-score	support
0	0.95	1.00	0.98	21
1	1.00	0.96	0.98	24
2	1.00	1.00	1.00	10
3	1.00	1.00	1.00	17
accuracy			0.99	72
macro avg	0.99	0.99	0.99	72
weighted avg	0.99	0.99	0.99	72

VII. CONCLUSION

Raw cotton wool images are highly used in Raw Cotton Image Classification. In this method, colour features are extracted from the raw images to classify the Grade of cotton wool. CNN uses colour features to classify the signal into three types, namely Grade I, Grade II and Grade. The Accuracy, Precision, Recall and F1-score of the classifiers are calculated by using the proper performance measurement. The experimental result shows that the CNN has the good performance while compared to the other classifier with the combined features. Proposed work has given a success rate of accuracy 83.33%, Precision 99%, Recall 100%, and F1 score achieved 99% with the average computational time 16.47 seconds per image on cotton wool. The results showed that the proposed system performed better by comparing to the previous research works.

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