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DETECTING FRAUDULENT LABELING OF SEED SAMPLES USING COMPUTER VISION

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Abstract
Every grower in agriculture domain, at some point, observes the Poor seed quality has several implications, including late growth, damping out, poor growth, weak young plants, and mixed or ethnically compromised batches. The purpose is to have good quality and quantity crop seeds from it marketing point of view. Selection of right seeds can make it possible. Until now, all this has been handled manually, but machine vision approach can result better in this regard. Cotton, Wheat and Corn crops are widely cultivated in southern Punjab as well as throughout the world to produce various consumable and wearable items. Since seeds of these crops are evaluated in many areas with the aims of sowing and further processing, they should be identified in expedite and accurate manner for the selection of seed. In this research activity, an affordable machine vision approach has been investigated to classify types of wheat seeds. The experiments have been performing on the dataset collected from agriculture research center of Bahawalpur, Pakistan. Types of wheat seeds were annotated and labelled by the domain experts. Several Knowledge sets, algorithms, and algorithms for learning predictors have been investigated to get the best predictive m1odel for wheat seeds classification. Training and test sets have been used to tune the model parameters. Resultantly, fast and accurate operations have been adopted to serve agricultural industries. For quantitative assessment of the research work, standard evaluation parameters, accuracy, specificity and sensitivity have been used. The developed system achieved an overall accuracy as (98.60%).

1.1 Introduction
The climate of Pakistan is helpful for agriculture. The circumstances are appropriate for cultivation of numerous kinds of yields. Wheat is one of the major crop of Pakistan. Wheat is one of the four main agricultural harvests in Pakistan, i.e., cotton, rice, and sugarcane with eighty percent of Agriculture Cultivating it on an area of around nine million hectares throughout the winter or "Rabi" period [1]. Wheat is the most significant steady diet yield consumed by almost more than thirty percent of global population of the world populace and provides extra proteins and calories than other food.[2]. It is nourishing, simple to transport and store and be able to be prepared into different kinds of nourishment [3]. Wheat is

deliberated a wellhead of protein, B-group vitamins, minerals and nutritional stuff [4], whereas, the ecological circumstances can influence nutritious composing of wheat particle with its important covering of fiber, minerals and vitamins; this one is an amazing wellbeing constructing nourishment [5]. Wheat is an invaluable resource of carbohydrates [2].The flour of wheat is used to make confectionary products, energetic gluten of wheat and bread [6-9]. Current bread varieties of wheat have been cross-bred to hold larger quantities of gluten [10]. It is additionally used as animal food [11],wheat lager fermenting, for ethanol creation [12], wheat created crude bedding material for beautifying agents, the protein of wheat in meat deputies' and to produce wheat straw combinations[13]. Wheat grain and wheat germ be able to a decent source of nutritional fiber facilitating in the anticipation[14]. The phytochemical content and antioxidant activity were concentrated in processed particle of eleven assortments [15], which integrated a scope of durum wheat and white and red wheat. Whole wheat bread suitable for well-being [16]. Here is there is no doubt that adaptability is unparalleled. revenues of wheat have supplementary to its fortune [17]. The main trademark, which has certain it a benefit over other calm harvests, is the special things of batter framed from flour of wheat, which permit this one to be handled into a scope of breads other heated items and bread (counting rolls and cakes), noodles and pasta, and other handled nourishments [18]. Crop agriculture originated more than 10,000 years before on the flood grasslands of the great rivers of North Africa and the mid-East with man's detection of the propagative function of seed [19]. From the commencement of crop farming to our time, seeds have been the key component in the establishing, expansion, modification and enhancement of crop production [20]. However, seeds are such a basic part of agriculture we incline to take them for contracted, or overlook their vital roles in agricultural fabrication and crop improvement**.** Seeds are, initially, a most proficient and operative means of crop proliferation [21]. They are the primary means by which plant populaces have been and are scattered over both space and time [22]. Wheat is a grain yields .It originally originates from the Levant area of the Ethiopian Highlands and Near East, however it extent in time and is now nurtured worldwide [23]. Wheat is grownup occupying more land than anything else marketable food [24]. That one is also the most traded yield, much greater than all trade of the other yields combined [25-48]. It is also used as a livestock feed, and its chaff is used as a construction material [49]. It is used for many purposes but primarily for foods. Wheat is used for making flour for altered kinds. Wheat feeds billions of people and animals round the world [50].

Wheat, as created by natural surroundings, comprises multiple remedial merits. All aspects of entire wheat particle provides elements needed by human body [2]. Gluten and starch in wheat give vitality and warmth.[51]; the internal grain pelts, Phosphorus [52] and other inorganic salts; the exterior wheat,truly necessary The material is unpleasant, which makes it easier simple improvement of entrails; nutrients B and E, the germ [53]; and protein of wheat helps manufacture and fix strong tissue [54]. The grain's seed, which is expelled in the procedure of refining [55], is likewise plentiful in basic nutrient E, a shortage of which can cause cardiovascular disease [56-76]. Loss of nutrients and inorganic in the sophisticated flour of wheat has prompted far reaching preponderance of blockage and supplementary stomach related disturbing dietary issue and influences [77]. Entire wheat, that incorporates wheat germ and grain, thusly, gives insurance against diseases e.g., constipation, ischaemic, heart disease, disease of the colon called diverticulum, appendicitis, diabetes and obesity [78]. In 2019, wheat fabrication for Pakistan was 24.3 million tonnes. Wheat fabrication of Pakistan increased from 7.294 million metric tonnes in 1970 to 24.3 million tonnes in 2019 increasing at an average annually rate of 2.83 percent [79]. All sorts of seeds are the foundation of the agricultural sector. Although technology has streamlined many of the day-to-day operations of cultivation, yields and crop quality would suffer substantially without a consistent supply of high-quality seed. Seed quality has a substantial impact on agronomic and agricultural crop productivity [80]. Using seeds of excellent quality is one of the most important factors in enhancing crop productivity in any cultivation framework [81].

The computer knowledge is updating day by day with new improvements, such as new and efficient methods to data acquisition, processing, analysis, and representation, which have limitless consequences in the farming graphics field. Machine learning gives detailed information about seeds of crops essential for harvest follow up. Computer vision is a primary approach classification and grading of seeds. The forthcoming and accessible techniques of artificial intelligence (AI) are making supports in deciding whether seeds are best quality or not. Using computer vision and machine learning models, wheat type classification can be performed [82-114].

The properties of the problem of automatic fraudulent detection of seeds make it an outstanding research problem in food production, imagery analysis, and pattern recognition. The initiative of this learning is to research strategies that could mechanically detect fraudulent labeling of seeds. There is a need of this knowledge in various fields particularly in The farming field to assist agricultural practitioners in the process of diagnosing the quality of seeds This computer-mediated automated system will enable them in detect fraudulent labeling of seeds diagnosing process without going through the manual time consuming and complex processes. Seeds are the foundation for cultivating fields. Wheat seed types are problematic to distinguish accurately by sight checkup. So, corrupt dealers could simply adulterate or mislabel of high quality wheat seed with less valued collections that appearance alike. We necessity an approach to monitor the interests of our exchange accomplices. Following are the fundamental objectives of the proposed technique.

a) To provide a computer based fully automated way for the detection of fraudulent labeling of seeds. b) To decrease figuring/time to diagnose quality of seed. c) To inspect the effect of computer vision in agriculture imaging modalities. d) To design a method that is more accurate and forceful than the approaches already exist. e) To discover potentials of developing robust way for classification and grading of seeds. f) To study relatively applicability and implementation of different seeds image classification and segmentation methods and finally apply which is greatest one.

To extent the performance, robustness and effectiveness of the planned top down method. The presentation is known in expressions of TN rate by using following formulas (specificity) TN/(TN+FN), true positive rate (sensitivity) TP/(TP+FN), and (accuracy)(TN+TP)/(TN+TP+FN+FP) where TN is true negative, FN false negative, TP true positive and FP is false positive. The breakdown of this article is planned as follows. In chapter no.2, literature reviewed has been positioned. While methodology has been placed in chapter no.3. Chapter no.4 has results achieved through the proposed technique along with their discussions. Conclusion along with future remarks is presented in the last chapter of this article.

2 Literature Review

Computer vision is an interdisciplinary discipline those treaties with in what way machine be able to made to increase significant level comprehension from vedio and digital image. From a technical perspective, it seeks to mechanize duties that humans bear optical organism can do.[115] Computer vision is concerned with the programmed extraction, examination and nice of helpful data from a single picture or an arrangement of pictures. It comprise of the development of a hypothetical and algorithmic premise to achieve programmed visual comprehension [116].

As an intelligent educate, computer vision is worried about the speculation behind artificial frameworks that remove information from pictures. The picture data can take different sizes, for example, video collections, views from multiple cameras, or multichannel data from a diagnostic diagnostic [116]. The machine's vision oversees the process of taking, caring for, evaluating, and retrieving images. It converts images into multidimensional numerical or representational data that can be used to make decisions and modernize mechanical processes that rely on visual judgment. Computer vision is related to the hypothesis of artificial frameworks, which pit data from photos. A critical idea for advancing the computer vision sector is to replicate the human eyesight capabilities using electronic seeing and data of a picture [117].

The authors [118] have conducted a research for the classification of wheat kernel. Two datasets were used in their investigations 1) a customized dataset obtained from department of seed production and plant breeding University of Warmia and Mazury in Olsztyn, Poland.

2) Locally developed dataset. First dataset consists of T.dicoccum, T.monococcum, T.polonicum, T.durum, T.spelta and T.aestivum ssp. Aestivum types of wheat types, photographs of The grain seeds were brought with an advanced camera Sony ILCE 5100.

In another study conducted by [119], the study descirbed the prunus sp. seeds classification. They conducted studies on 1,393 P. domestically seeds of 19 traditional Sardinian species from the CNR-ISPA field list (Nuraxinieddu, OR, Sardinia) and four commercial cultivars, 'Mirabolano Giallo' and 'Mirabolano Rosso' (Prunus cerasifera Ehrh.) and 'Shiro' (Prunus salicina Lindl.). For their testing, they used two machine learning models, namely KNN and LDA. At long last, for two last datasets, they formed by combining all possible data, accuracy obtained is 0.8190%.

In another method, investigated by [120], rapid classification of wheat grain varieties has been performed. The dataset has been obtained from Anhui Longping High Tech Seed Industry Co., Ltd. in Hefei, Anhui province, China. They used methods 1) Principal component analysis (PCA). 2) LDA. 3) SVM. 4) ELM. They obtained accuracy up-to 91.3%.

[121] have classified cowpea seeds using machine learning and computer vision. They used datasets consists of 501 cowpeas seeds formed in Egypt during 2017 belongs to assortment accepted by the Egyptian Ministry of farming and land recovery. They used LDA based models. With results, precision has been chosen as an expected progress metric as 96.76%, 97.51% and 97% and overall correct classification (OCC) respectively. The results revealed that LDA models had good accuracy in differentiating ‘Aged’ and ‘Non-aged’ and OCC, i.e., 81.80%, 79.05% and 81.0% respectively. Table 1 described the state-of-art of Using artificial intelligence to identify samples of seeds with bogus labels.

Table 1: State of the Art

Sr No	Author, Year	Problem Addressed	Dataset Detail	Methodology	Evaluation
01	Martín-Gómez, José Javier, et al. (2019) [118]	classification of wheat kernels	Two datasets (a) customized dataset obtained from department of seed production and plant breeding University of Warmia and Mazury in Olsztyn, Poland (b) locally developed dataset	1. An ellipse of aspect ratio (AR) is 1.8 2. An ellipse of AR is 2.4 3. A lens of AR is 3.2	J index
02	Frigau, Luca, et al.(2019) [119]	Classification of Prunus sp. seeds	1,393 a seeds P. domestic obtained from 19 customary Sardinian cultivars CNR-ISPA (Nuraxinieddu, OR, Sardinia	Classifiers 1. k-Nearest Neighbour (KNN) 2. Linear Discriminant Analysis (LDA)	The average accuracy is 0.8190.
03	Bao, Yidan, et al.(2019) [120]	Rapid Classification of Wheat Grain Varieties	Dataset obtained from High Tech Seed Industry Co., Ltd., China.	1. (PCA) 2. (LDA) 3. (SVM). 4. (ELM)	Accuracy up to 91.3%

04	ElMasry, Gamal, et al.(2019)[121]	classification of Vigna unguiculata seeds	501 cowpeas seeds formed in Egypt during 2017 belongs to assortment approved by the Egyptian Ministry of farming	1. Linear discri-minant analysis (LDA)	Accuracy 96.76%, 97.51% and 97% for 'Non-germinate d', 'Germinated' and (OCC) respectively.
05	M. Khojastehnazh and and H. Ramezani(202 0) [122]	categorization of grapes in quantity	Dataset obtained from Bonab region, Iran	classifier 1. (SVM) 2. (LDA) 3. (PCA)	accuracy of modes I 85.55% & modes II 69.78%
06	Nie, Pengcheng, et al(2019)[123]	Classification of hybrid seeds	Dataset obtained from China, Academy of Agricultural Sciences, Zhejiang	Three methods are used PLS-DA SVM DCNN	uppermost classification accuracy, more than 95 percent of DCNN
07	Zhang, Tingting, et al.(2018)[124]	Determining Seed Viability of Wheat Seeds	Four spectral datasets, Datasets purchased Froma local market (Jinan,China)in October2017.	near-infrared and visible (NIR/ VIS) hyper spectral imaging methods, Classification models. PLS-DA SVM	Detection accuracy for grains more than 85.2 percent for viable grains more than 89.5 percent final germination of seed higher than 89.5%
08	[125]	classifictaion of diploid and haploid grain seeds	dataset consist on1770 diploid & 1230 haploid maize seed pictures	convolutional neural networks (CNNs) AlexNet, VVGNet, GoogLeNet & ResNet	The precision, specificity, F-score of VGG-19, quality index and sensitivity were 94.22 percent, 93.97%, 93.07%, 94.27% and 94.58%, respectively.

09	[126]	Automatic Classification of Chickpea Varieties	Dataset obtained in Kermanshah, Iran.	Two technique used for classification. 1. first technique is grounded on texture & color features abstraction (ANN-PSO) 2. The second technique is not grounded on an explicit abstraction of features.	The accuracy of 97.0% and the second technique achieved a CCR of 99.3%.

2.1 Research gap

Current state-of-the-art research findings are not entirely correct. There is a small dataset that researchers in this field uses for its studies. In the research, not all types (or maximum types) have been categorized. The kinds categorized in the research are not indigenous to Pakistani regions.

3 The Proposed Methodology

The dataset, preprocessing, set of rules and of proposed technique are discussed in this research. I have imposed my suggested grading technique on two types of grain seeds (Faisalabad-2008, and Zincol-2017).

3.1 Dataset

The dataset consisting of wheat seed images has been acquired from agriculture department Bahawalpur, Pakistan. Two classes of the dataset have been used for research and experiments such that Faisalabad 2008and Zincol-2017, as shown in Table 2. This dataset includes 1000 images of Faisalabad-2008 and 1000 images of zincol-2017. The resolution of the every image is 512*512 pixel.

Table 2: Dataset used for the experimental purpose

Sr#	Dataset	Types used in experiments	Total images used for experiments		Grand Total
			Training	Testing	
1	Regionally created information from the Department of Agriculture, Bahawalpur, Pakistan	Faisalabad-2008 and Zincol-2017	750/class	250/class	1000/class

3.2 Preprocessing

In the preprocessing phase, Before the photos were entered into the suggested model, specific steps were carried out. First, as illustrated in figure 1, resize the photographs to 512 x 512 in the "PNG" standard. In the second stage, as illustrated in figure 2, every image in this dataset has three channels: red, green, and blue. Together with the strength of each channel, the data from each of these channels has been retrieved. Resultantly, five channel from these images are there for experiments.

	
(a)	(b)
	
(c)	(d)
	
(e)	(f)

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(g)

(h)

(i)

(j)

Figure 1: sample single seed images of wheat types, (a) Faisalabad – 2008 Original Image (b) Zincol-2017 Original Image (c) Faisalabad – 2008 Intensity Channel Image (d) Zincol-2017 Intensity Channel Image (e) Faisalabad – 2008 Red Channel Image (f) Zincol-2017 Red Channel Image (g) Faisalabad – 2008 Green Channel Image (h) Zincol-2017 Green Channel Image (i) Faisalabad – 2008 Blue Channel Image (j) Zincol-2017 Blue Channel Image

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(a)

(b)

(c)

(d)

(e)

(f)

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(g)

(h)

(i)

(j)

Figure 2: sample multiple seed images of wheat types, (a) Faisalabad – 2008 Original Image (b) Zincol-2017 Original Image (c) Faisalabad – 2008 Intensity Channel Image (d) Zincol-2017 Intensity Channel Image (e) Faisalabad – 2008 Red Channel Image (f) Zincol-2017 Red Channel Image (g) Faisalabad – 2008 Green Channel Image (h) Zincol-2017 Green Channel Image (i) Faisalabad – 2008 Blue Channel Image (j) Zincol-2017 Blue Channel Image

3.3 The Proposed Convolutional Neural Network Architecture

In all types of image processing, CNN, a type of deep learning [127] has been widely used. CNN has been used for the classification of wheat seeds in this article. Additional names for these include complicated deep feed forward artificial neural networks [113]. Different levels of local perspective granularity can be used by CNN to identify spatial connections [114]. CNN has achieved great success in many areas, including as word recognition in natural images [113], handwriting recognition [116], and image categorization [115].CNN was proposed by computer scientist Yann LeCun in the late 1990s [117]. It drew inspiration from how people recognize objects with their eyes. CNN's excellent accuracy has led to its widespread application in jobs involving document identification, identification of handwriting, recognizing objects, and image categorization. Initial processing is far less necessary with CNN than with other classification methods.Figure 3.3 displays the CNN-based design that has been suggested.

3.3.1 Image Input Layer

The first layer of the suggested model is a picture input layer, where the image sizes are specified. Each image in each test has the dimensions 512*512*1, which stand for height, width, and channel size, respectively.

3.3.2 Convolutional Layer

The CNN's most crucial layer is the convolutional layer. After convolving the input, convolutional layers forward the result to the subsequent layer. This is comparable to how an auditory cortex neuron reacts to a particular stimulation [118]. Three 2D convolutional layers have been used in the suggested methods. The filter size and number of filters in the convolutional layer are determined by the first and second parameters, respectively. Eight filters of size 3*3 (height*width) have been employed in the first multilayer layer. A total of sixteen filters with a 3*3 dimension have been employed in the second convoluted layer. A total of 32 filters with a 3*3 filter size have been employed in the third convoluted layer. Figure 3 illustrates how this layer extracts a new matrix by performing a dot product calculation between two matrix elements, such as the image being input and kernel. The convolution layer's primary goal is to identify attributes from input images. The convolution process aids in decreasing noise, edge recognition, motion blurring, correction, and other tasks that might assist the machine to identify distinctive features in a picture.

3.3.3 Batch Normalization Layer

Three batches of layers of normalizing have been employed in every investigation conducted for the purposes of this study. Between convolutional neural and ReLU layers, simultaneous normalization layers have been employed to decrease sensitive and speed up the learning of networks.

3.3.4 ReLU Layer

The ReLU layer is the next level utilized in studies after the batch equalization layer. The suggested model makes use of a total of three ReLU layers. ReLU is an acronym for rectifying linear unit. The activation function, such as max (0, x), will be applied element-by-element in this layer. The negative numbers in the stimulation matrix are eliminated by the ReLU layer by setting them to zero.

3.3.5 Pooling Layer

Reducing characteristics is necessary since the jumbled image is too big. Reducing the size of an image without sacrificing structure or features is the primary function of the layer that pools images. Two maxpooling2dlayers have been employed in this work. The maximum element from the corrected highlighted map is returned by max pooling. The corrected map of features in these studies has a dimension of [2,2].

3.3.5 Fully Connected Layer

This layer has been utilized in these trials to recognize the more extensive patterns in an image by combining the parameters of all the layers prior to it.

3.3.6 Softmax Layer

The result of the fully linked layer has been normalized using the function of soft max activation. The output of the softmax layer consists of positive values that add up to one, which the categorical layer uses as potential classifications.

3.3.7 Classification Layer

The final layer is the categorizing layer, which assigns an object categorization to the input visual.

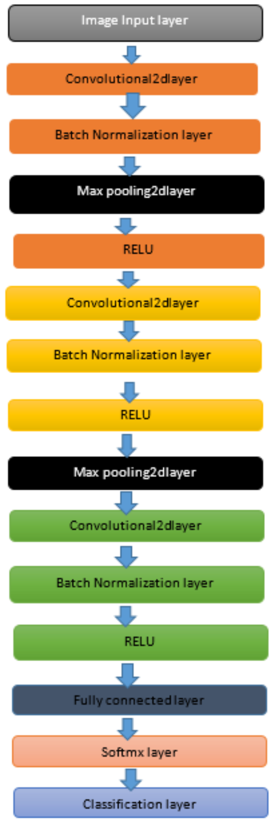

Figure 3: The proposed CNN based architecture for wheat seeds types classification

4 Result and Discussion

In chapter 3, stage by stage description of the approach adopted by the proposed system has been presented. Results achieved through the suggested approach has been presented in this chapter no.4.

4.1 Results

Results got through the suggested methodology has been presented in this section 4. The results of the research were retrieved using MATLAB R2019b. The dataset consisting of wheat seed images has been acquired from agriculture department Bahawalpur, Pakistan. Two classes of the dataset have been used for research and experiments such that Faisalabad-2008 and Zincol-2017. This dataset includes 1000 images of Faisalabad 2008 and 1000 images of zincol-2017. The resolution of the every image is 512*512 pixel. All the images of dataset have RGB, gray level and three channels, i.e., red, green and blue. In all RGB, gray level and three channels equal information has been embodied, and it was an overhead to process the information contained in all three channels. In the preprocessing phase, this overhead is removed by considering only one channel of these images. The dataset has been split into sets for training as well as testing for research reasons. There are 750 photographs in the learning set and 250 images in each class in the assessment set. Total five experiments have been performed in research work as follows;

1. Experiment no.1 performed on original wheat images seed two-types.
2. Experiment no.2 performed on intensity channel wheat images seed two-types.
3. Experiment no.3 performed on red channel wheat images seed two-types.
4. Experiment no.4 performed on green channel wheat images seed two-types.
5. Experiment no.5 performed on blue channel wheat images seed two-types.

4.1.1 First experiment

In the first experiment, 1000 original RGB images Faisalabad-2008 and 1000 original RGB images of Zincol-2017 have been used. In training phase, 9 epoch and maximum 99 iteration. 750 images in training and 250 images in testing set are automatically selected for every class. In the first investigation, accuracy was effectively attained 95.40%. Figure 4 shows epoch wise accuracy and error rate of first experiment.

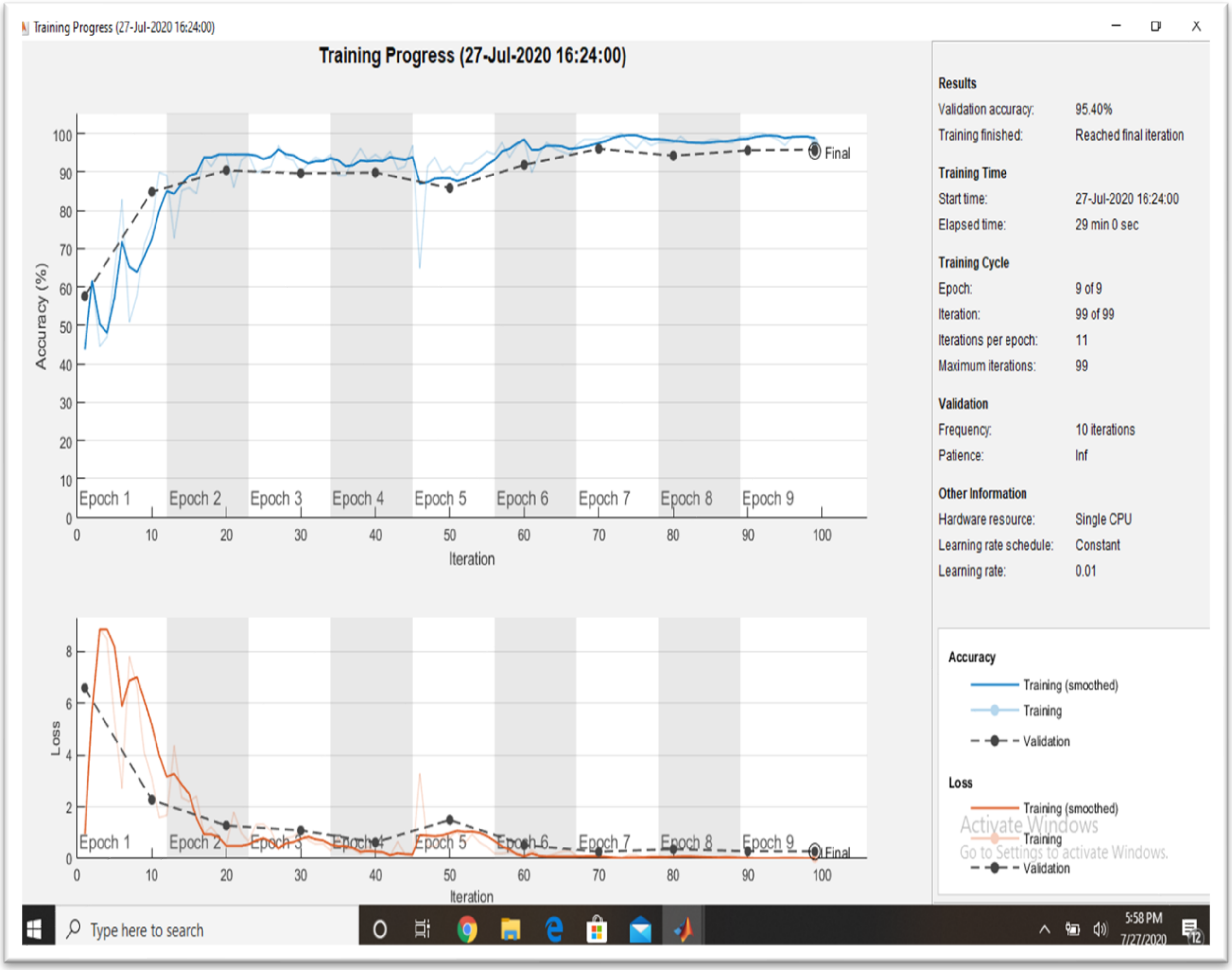

Figure 4: Epoch wise accuracy and error rate of first experiment

4.1.2 Second experiment

In the second experiment, 1000 intensity channel images Faisalabad 2008 and 1000 intensity channel images of zincol-2017 have been used. In training phase, 9 epoch and maximum 99 iteration. 750 images in training and 250 images in testing set are automatically selected for each class. The second experiment successfully achieved accuracy 96.60% figure 5 shows the result of second experiment.

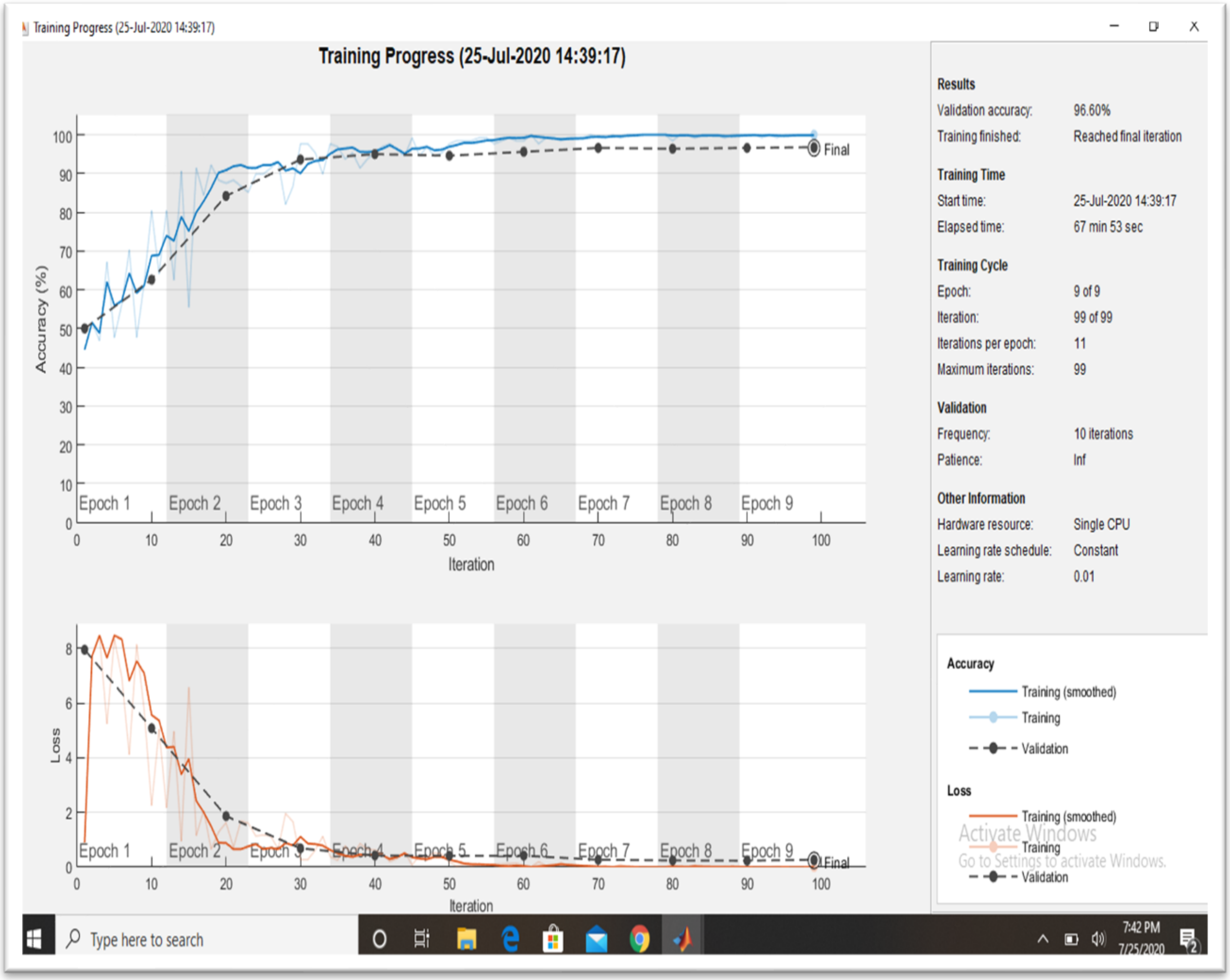

Figure 5: Epoch wise accuracy and error rate of second experiment

4.1.3 Third experiment

In the third experiment, 1000 red channel images Faisalabad-2008 and 1000 red channel images of zincol-2017 have been used. In training phase, 9 epoch and maximum 99 iteration. 750 images in training and 250 images in testing set are automatically selected for every class. The third research was effective in achieving precision 93.40%. Figure 6 displays the third test's epoch-wise performance and percentage of errors.

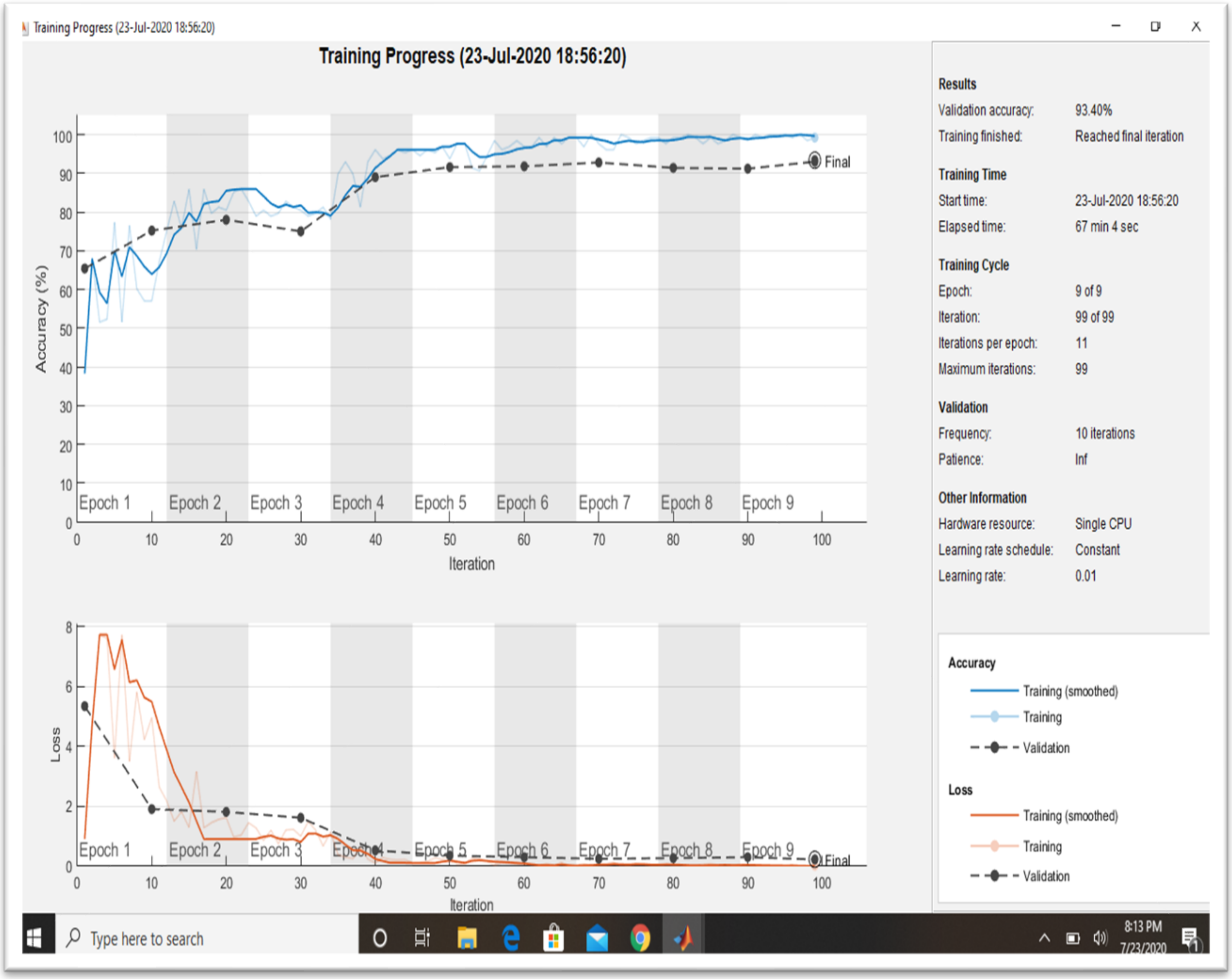

Figure 6: Epoch wise accuracy and error rate of third experiment

4.1.4 Fourth experiment

In the fourth experiment, 1000 green channel images Faisalabad 2008 and 1000 green channel of zincol-2017 have been used. In training phase, 9 epoch and maximum 99 iteration. 750 images in training and 250 images in testing set are automatically selected for every class. The fourth research was effective in achieving precision 98.60%. Figure 7 displays the third test's epoch-wise performance and percentage of errors.

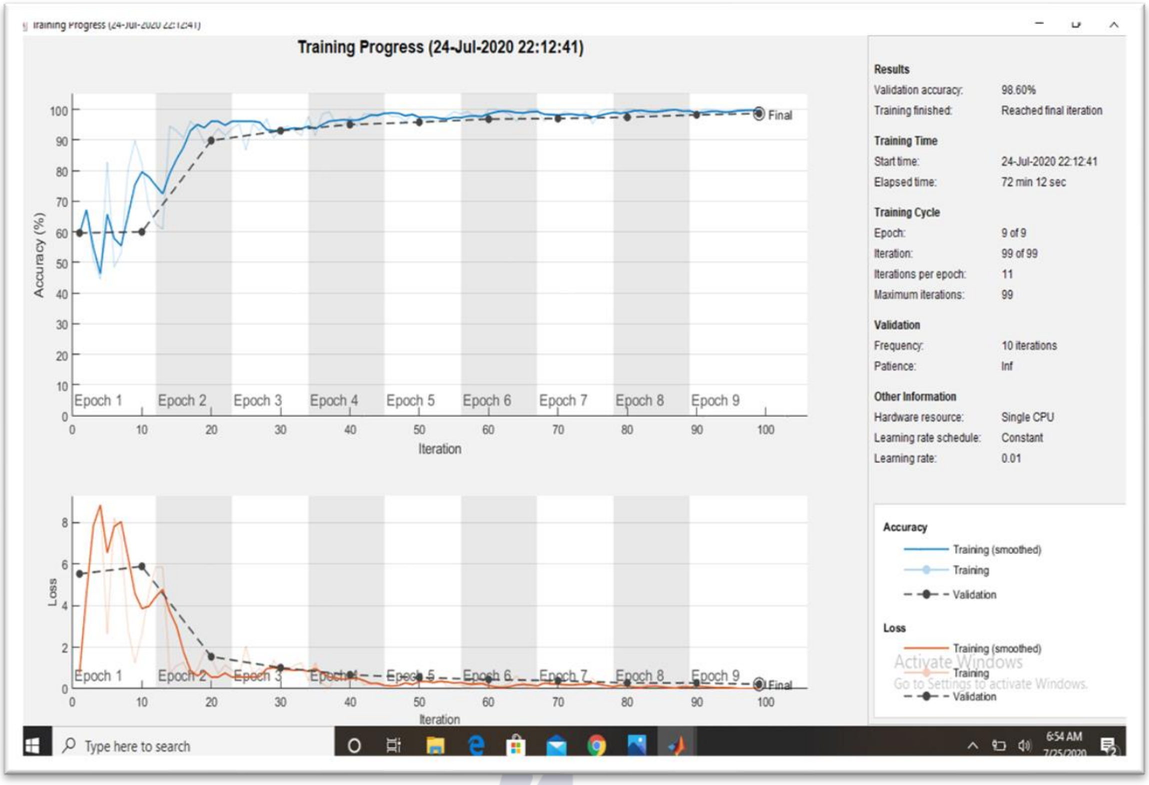

Figure 7: Epoch wise accuracy and error rate of fourth experiment

4.1.5 Fifth experiment

In the fifth experiment, 1000 blue channel images Faisalabad 2008 and 1000 blue channel images of zincol-2017 have been used. In training cycle, 9 epoch and maximum 99 iteration (11 iterations per epoch). 750 images in training and 250 images in testing set are automatically selected for each class. The fifth research was effective in achieving precision 90.60%. Figure 8 displays the third test's epoch-wise performance and percentage of errors.

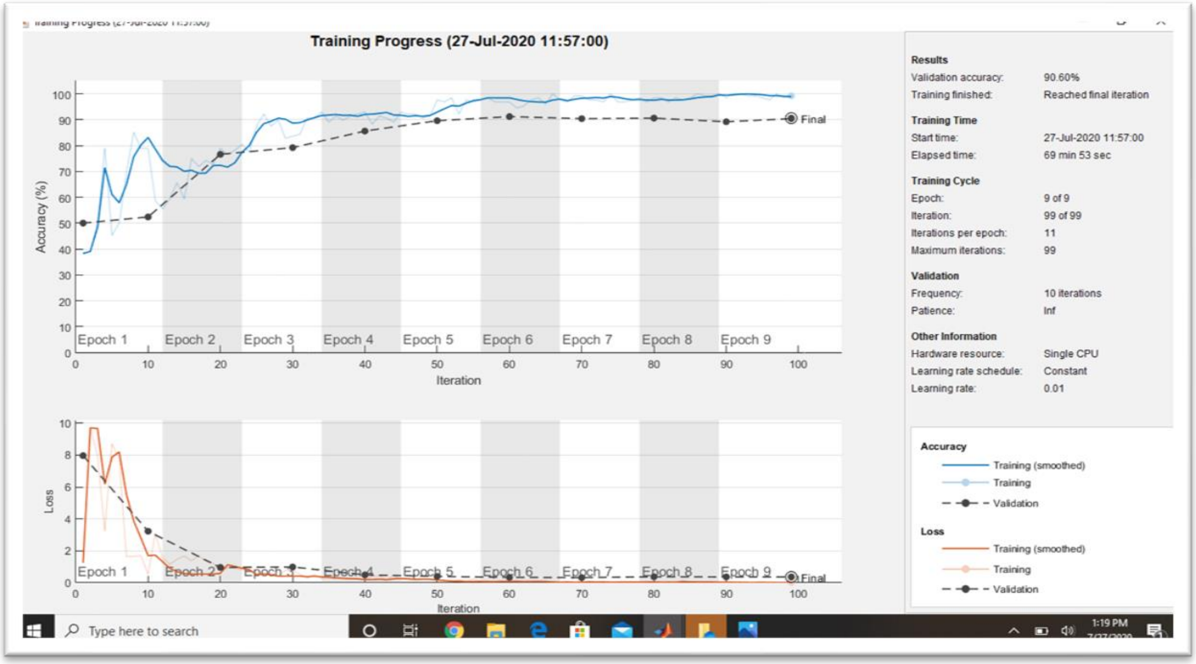

Figure 8: Epoch wise accuracy and error rate of fifth experiment

Table 3: Result obtained through the proposed model in all five experiments

S. No.	Experiment No.	No. of Images Used	Accuracy	Spec.	Sens.
1	Experiment no 1	1000 per class	95.40%	97.10%	93.82%
2	Experiment no 2	1000 per class	96.60%	98.34%	94.98%
3	Experiment no 3	1000 per class	93.40%	93.93%	92.89%
4	Experiment no 4	1000 per class	98.60%	98.41%	98.80%
5	Experiment no 5	1000 per class	90.60%	92.47%	88.89%

4.2 Discussion

In this thesis, total five experiments are performed. The first experiment has achieved accuracy 95.40% and second, third, fourth, and fifth experiments achieved accuracy 96.60%,93.40%, 98.60% and 90.60% respectively. The comparison of the results with state-of-the-art methods is shown in Table 4.

4.2.1 Comparison with state-of-the-art methods

Table 4 presents a comparison between the outcomes of the state-of-the-art procedures and the results achieved using the suggested method. The issue of identifying false labeling of rice samples and fuzzy categorization knowledge databases has been tackled by the research project carried out by (Ali et al., 2017) The standard accuracy for classification of their suggested model was more than 90%.

In another method, (Cinar & Koklu, 2019) classification of rice varieties using artificial intelligence methods. Achievement rates in the classification attained 93.02% (LR), 92.86% (MLP), 92.83% (SVM), 92.49% (DT), 92.39% (RF), 91.71% (NB) and 88.58% (k-NN). Kurtulmuş et al., 2016) have classified of pepper seeds. The level of accuracy was attained 84.94%

using the (SFS). In another recent study conducted by (Altuntaş et al., 2019), identification of haploid and diploid maize seeds. The accuracy, specificity, sensitivity, F-score of VGG-19 and quality index, were 94.22%, 93.97%, 94.58%, 93.07% and 94.27% respectively. Our proposed system achieved overall accuracy is 98.60%. The proposed method outperformed current methods and obtained the maximum efficiency value., i.e., 98.60%, which is the best results achieved so far as per our knowledge.

Table 4: Comparison of the result with state-of-the-art methods

Sr.No	Author Name and year	Proposed Methodology	Dataset used	Classification	Evaluation Measure
1	(Ali et al., 2017)	Neural network based approach	Datasets contains six different varieties Super-Kiynat and Super- Kernel as basmati samples and IRRI-9, IRRI-Fine, Superi and IRRI-6 as non basmati samples	Detecting fraudulent labeling of rice samples, fuzzy classification knowledge database	The average classification accuracies greater than 90% of Six varieties.
2	(Cinar & Koklu, 2019)	Models used LR, MLP , SVM, DT ,RF, NB and kNN	Dataset contain 3810 images of rice grains.	Classification of Rice Varieties Using Artificial Intelligence Methods	Achievement rates in the classification attained 93.02% (LR), 92.86% (MLP), 92.83% (SVM), 92.49% (DT), 92.39% (RF), 91.71% (NB) and 88.58% (k-NN).
3	Kurtulmuş et al., 2016)	Differentiate pepper seed based on NN and computer vision. Python 2.7 programming language was used for image processing steps	The grains were acquired from a local seed source in Turkey in 2013	Classification of pepper seeds	The level of accuracy was attained 84.94% using the (SFS).

4	(Altuntaş et al., 2019)	convolutional neural networks (CNNs) AlexNet, VVGNet, GoogLeNet & ResNet	dataset consist on 1230 haploid & 1770 diploid maize seed images	Identification diploid and haploid maize seeds.	The accuracy, specificity, sensitivity, F-score of VGG-19 and quality index, were 94.22%, 93.97%, 94.58%, 93.07% and 94.27% respectively
5	The Proposed methodology	CNN	Locally developed dataset from agriculture department, Bahawalpur, Pakistan	Detecting fraudulent labeling of seeds samples	Accuracy=98.60%

5 Conclusion

In this research work, a CNN based architecture has been proposed to classify the type of wheat seeds. Two classes, i.e., Faisalabad-2008 and Zincol-2017 have been classified. Experiments have been performed in five different ways, 1) Experiment no.1 performed on original RGB wheat images seed of two-types.2) Experiment no.2 performed on intensity channel wheat images seed of two-types.3). Experiment no.3 performed on red channel wheat images seed of two-types.4) Experiment no.4 performed on green channel wheat images seed of two-types.5) Experiment no.5 performed on blue channel wheat images seed of two-types. Experiment No.1, experiment No.2, experiment No.3, experiment No.4 and experiment No.5 have achieved the accuracy as 95.40%, 96.60%, 93.40%, 98.60% and 90.60% respectively. The suggested approach attained the finest precision to the best of our knowledge, as demonstrated empirically. The algorithm will be able to classify potentially all varieties of wheat seeds that are grown in Pakistan, particularly in Punjab and south Punjab, in further study. In addition, the model will be improved in terms of the metrics it has attained.

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