Proceedings of the Pakistan Academy of Sciences:
A: Physical and Computational Sciences 58(2): 1–10 (2021)

ISSN (Print): 2518-4245; ISSN (Online): 2518-4253
https://doi.org/10.53560/PPASA(58-2)692

Pakistan Academy of Sciences

Research Article

Automated Corn Seed Fusarium Disease Classification System Using Hybrid Feature Space and Conventional Machine Learning Techniques

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Abstract: The purpose of this learning is to detect the Corn Seed Fusarium Disease using Hybrid Feature Space and Conventional machine learning (ML) approaches. A novel machine learning approach is employed for the classification of a total of six types of corn seed are collected which contain Infected Fusarium (moniliforme, graminearum, gibberella, verticillioides, kernel) as well as healthy corn seed, based on a multi-feature dataset, which is the grouping of geometric, texture and histogram features extracted from digital images. For each corn seed image, a total of twenty-five multi-features have been developed on every area of interest (AOI), sizes (50 × 50), (100 × 100), (150 × 150), and (200 × 200). A total of seven optimized features were selected by using a machine learning-based algorithm named "Correlation-based Feature Selection". For experimentation, "Random forest", "BayesNet" and "LogitBoost" have been employed using an optimized multi-feature user-supplied dataset divided with 70% training and 30 % testing. A comparative analysis of three ML classifiers RF, BN, and LB have been used and a considerably very high classification ratio of 96.67 %, 97.22 %, and 97.78 % have been achieved respectively when the AOI size (200×200) have been deployed to the classifiers.

Keywords: Fusarium Disease, Corn Seed, LogitBoost, Machine Learning.

1. INTRODUCTION

Corn (Zea mays), also called Indian corn or maize, is a cereal plant of the Poaceae family and its edible grains. Homegrown culture began in the Americas and is quite possibly the most generally circulated food crop on the planet. Corn is utilized as creature feed, human food, biofuel, and mechanical crude material. In the United States, the colourful variegated strains called Indian corn are customarily utilized for improvements collected in harvest time [1]. Around 10,000 years prior, the native people groups of Mexico initially trained corn. The male bloom develops on the panicle

Received: October 2019; Accepted: June 2021
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toward the finish of the principal shaft of the stem [2]. The (female) inflorescences develop until they become consumable spikes, thick spikes with longitudinally masterminded spikelets; each pair of spikelets generally creates two lines of grain. Yellow and white corn assortments are the most mainstream food sources, even though there are additional assortments with red, blue, pink, and dark particles, ordinarily with streaks, spots, or streaks. Every ear is encircled by altered leaves called cases or units. Numerous mechanical corn assortments have been hereditarily changed to oppose the herbicide glyphosate or produce protein from Bacillus thuringiensis to murder certain nuisances. Furthermore, a few strains have been hereditarily adjusted to improve dry spell resilience [3].

Kernel area dependent commercial characterizations include brand name corn, grain corn, flour corn, sweet corn, and popcorn. The characteristic of chipped corn is that the crown of the grain is jagged, due to the sporadic drying of the hard and delicate starches that make up the grain. Silica corn with a modest amount of mild starch has no kernels. Cornmeal is mainly composed of mild starch, which has a delicate, fine grain that is effortlessly crushed [4]. Sweet corn has light wrinkled seeds; vegetable sugar does not turn into starch like various types. Popcorn is a limited corrosive type of corn. It is represented by small hard grains without mild starch. Heating will cause the water to grow in the cells, causing the grains to explode. The improvement of the corn is the consequence of the crossing, to cross strains of good parentage [5]. Although it is an important food in many parts of the world, the health benefits of corn are lower than those of other grains. It has a powerless protein quality and needs niacin. Diets that depend on it normally cause pellagra (lack of niacin). Its gluten (elastin) is of medium-low quality and is not used to make sourdough bread. However, it is widely used in Latin American cuisine to make masa, a dough used for varieties of staple foods such as tortillas and tamales. Since cornmeal does not contain gluten, it cannot be used on its own to make leavened bread. In the United States, corn is boiled or roasted on the cob, made into cream, made into cornmeal (hulled wheat) or flour, then cooked into corn pudding, porridge, polenta, meatballs, cornbread, and ground corn. It is also used for popcorn, candy, and other oatmeal products [6].

Corn is also used to produce (ethanol), which is the source of fluid biofuel. In the United States, corn ethanol is generally mixed with gas to create "gas liquor," a vehicle fuel made up of 10% ethanol. Even though corn-based biofuels were initially promoted as harmless to the ecosystem's choice of oil, their creation displaced arable land and raw materials from the evolved human lifestyle, sparking the joke of the "food for fuel" [7]. Cellulosic ethanol is made up of unappetizing plant parts such as rural waste and affects the natural hierarchy less than corn ethanol, although the innovative capacity for change is not normally as large as corn ethanol. The original of biofuels. Many pieces of the corn plant are used in industry [8]. Corn starch can be separated into corn syrup, which is a typical sugar and generally cheaper than sucrose; High fructose corn syrup is widely used in prepared food sources such as sodas and confectionery [9]. The auction is made of paper and wall panels; units are used as filling material; the ears are used outright as a fuel, used to produce coal and modern solvents. The portions of corn are prepared stew and the grains are immersed in a weakened corrosive sulfuric solution; thanks to dry treatment, corn shows up to steal water or steam; and during maturing the starch is transformed into sugar and the yeast is used to transform the sugar into liqueur. Corn husks [10].

1.1 Literature Review

The References [11] described the image processing techniques to grade three varieties of oranges (Bam, Khoni, and Thomson). Adaptive-Network-Based-Fuzzy-Inference-System method is used. The accuracy for Bam 3.7g, Khooni 1.28 g, and Thomson 3.2 g was measured. The References [12] described three stages in this paper for the classification and identification of plants. The first was pre-processing, the second was feature extraction and the third was classification. Different leaf features extracted for input vectors of ANN Artificial Neural Network. It gave 96% accuracy. This algorithm also gave 96% accuracy on both Flavia and ICL datasets. The References [13] proposed the work on pattern recognition techniques for accurate automated grading of oranges. That paper used two techniques. First was edited multi-seed nearest neighbor technique for sorting according to the size of oranges and achieved 90% accuracy and second was the linear regression-based technique for predicting the maturity level of oranges and achieved 98% result. The References [14] in this paper, several groups of textural characteristics of seed images were used to identify 9 diversities of common Wheat, Iranian seeds. For classification, the "Linear Discrimination Analysis LDA" classifier was contracted using the selected superior characteristics. The accuracy of the classification was reached 98.15% when the best 50 characteristics of the classifier were used.

2. MATERIALS AND METHODS

2.1 Data Collection

All the digital image corn seed dataset occupied from Yazman agriculture farm, Bahawalpur district of Punjab, Pakistan. Total six types of corn seed are collected which contain Infected Fusarium (moniliforme, graminearum, gibberella, verticillioides, kernel) as well as healthy corn seed. All the image datasets collected via the Canon Mirrorless DSLR Camera with 26 megapixels resolution at noon (12.00 pm - 2.00 pm) under pure climate and took twenty-five images of each seed types. The sample datasets are shown in Figure 1.

2.1.1 Image Pre-Processing

The collected dataset of various sizes can influence the outcomes. Thusly, individually image has been resized utilizing "MS Picture Manager". By utilizing this product, we have edited each picture and changed over into (510×510) pixels in height and width. The updated image dataset of similar size that is 150 (6×25) are explore in "CVIPtools version 5.7e " [15] and changed over into Gray-Level (8bit) format. Total four Area of interests (AOI's) having pixel measurements (50 × 50), (100 × 100), (150 × 150) and (200 × 200) have been made for each image and total of 100 (25 × 4) AOI's has been created on overall dataset as shown in Figure 2.

2.2 Methodology

The Digital image analysis tool "CVIPtool" has been used for experimentational work in which we extract "Texture Features", "Histogram Features", and "Geometric Features" from each AOI [16-18]. Exactly, 24 features were extracted from each AOI, which are clustered as 11 "Texture Features", 8 "Histogram Features", and 5 "Geometric Features" Statistically, it means that input data has been obtainable in 14400 (600×24) FVS for the individual size of corn seed image type.To acquire the optimal feature dataset, a feature reduction technique has been deployed. The detailed methodology shows in Figure 3.

2.2.1 Feature Reduction

It has been observed that all the extracted 24 features are not equally worthful for the experimentation

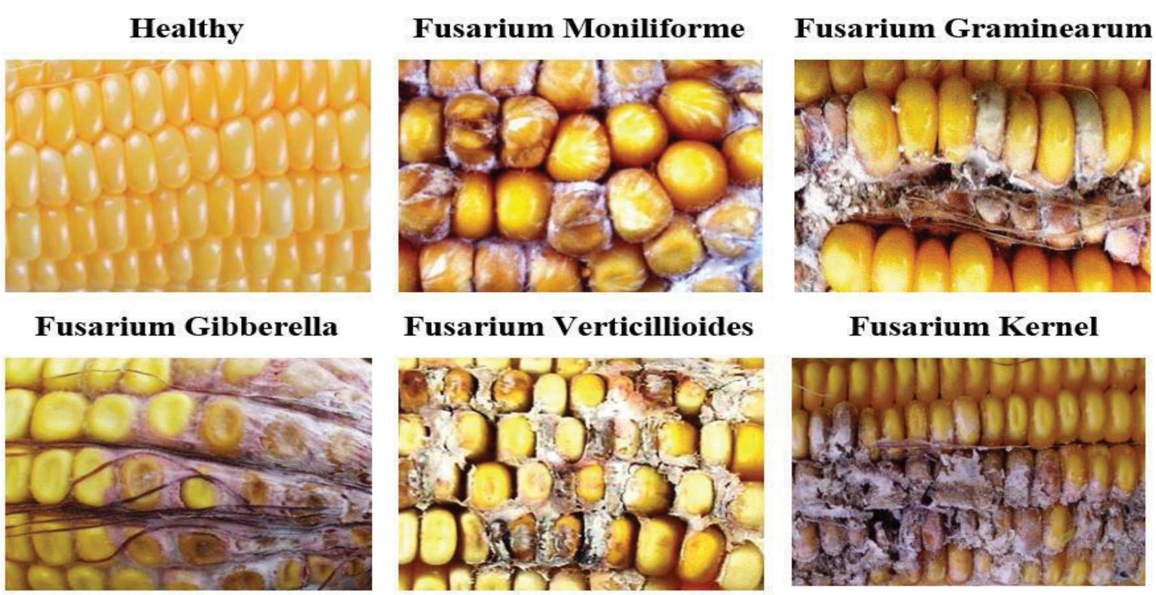

Fig. 1. Sample corn seed image dataset.

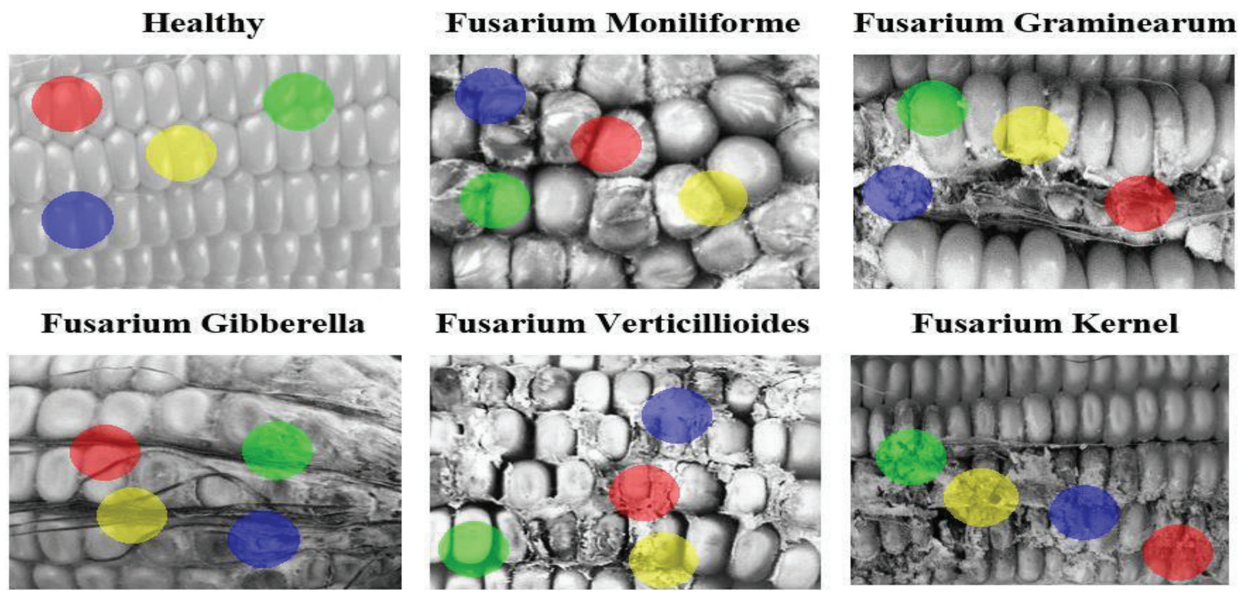

Fig. 2. Non overlapping area of interest on corn seed image dataset

and very difficult to deal with large FVS (that is 12000 multi-feature data space). For better response we must reduce this large FVS. So, we deployed "Correlation-based feature selection" "CFS" on corn seed dataset. The "CFS" has the facility to select the most projecting features in the dataset [19]. The CFS has been defined in Eq. 1.

$$H_F = \frac{M\overline{\sigma}_{cj}}{\sqrt{M + M(M-1)\overline{\sigma}_{jj}}} \quad (1)$$

2.2.2 Dataset

Two Datasets have been generated for experimentation training and testing purpose. In this study, six different types are used to classify twenty-five images size (512×512) of each type and four non-overlapping AOI's of sizes (50×50), (100×100), (150×150) and (200x200) are taken for each image. Total number of images are 100 (25×4) with four non-overlapping AOI's. Hence total six types are 600 (100×6) respectively which is selected as a dataset. Dataset has been divided into two parts 70 % and 30 % for training and testing purpose respectively. In training dataset, seventy instances are used while thirty instances are used in test dataset as per each variety. Total 420 (70×6) instances have been taken by training dataset to train a model while 180 (30×6) instances have been taken for test dataset shown in table 4.

2.2.3 Classification

For experimentation, ML classifier, "LogitBoost" (LB), "Bayes Net" (BN), and "Random Forest" (RF) has been employed because of 2 reasons: First, pre-defined corn seed types. Secondly, noisy input data, which is developed in ordinary atmosphere [20-21].

3. RESULTS AND DISCUSSIONS

The objective of this study is to classify the corn seed fusarium disease using ML approach and compare the results using LB, BN and RF classifiers. For this purpose, an image dataset of optimized multi-feature has been acquired for accurate and robust results. Some assessing parameter like "True Positive (TP)", "False Positive (FP)", "F-measure", "Matthews Correlation Coefficient (MCC)", "Receiver Operating Characteristic (ROC)", "Kappa Statistics", "Mean Absolute Error" (MAE) and "Root Mean Squared Error (RMSE)" have been observed [22-23].

At first step, the classification result on AOI's (50 × 50), (100×100), (150×150) was not satisfactory. An overall accuracy less than 88% have been observed using above discussed classifier namely LB, BN, RF. For acquiring satisfactory results, AOI's size has been increased and (200×200) ROI's size have been deployed for classification. A very promising result of corn seed

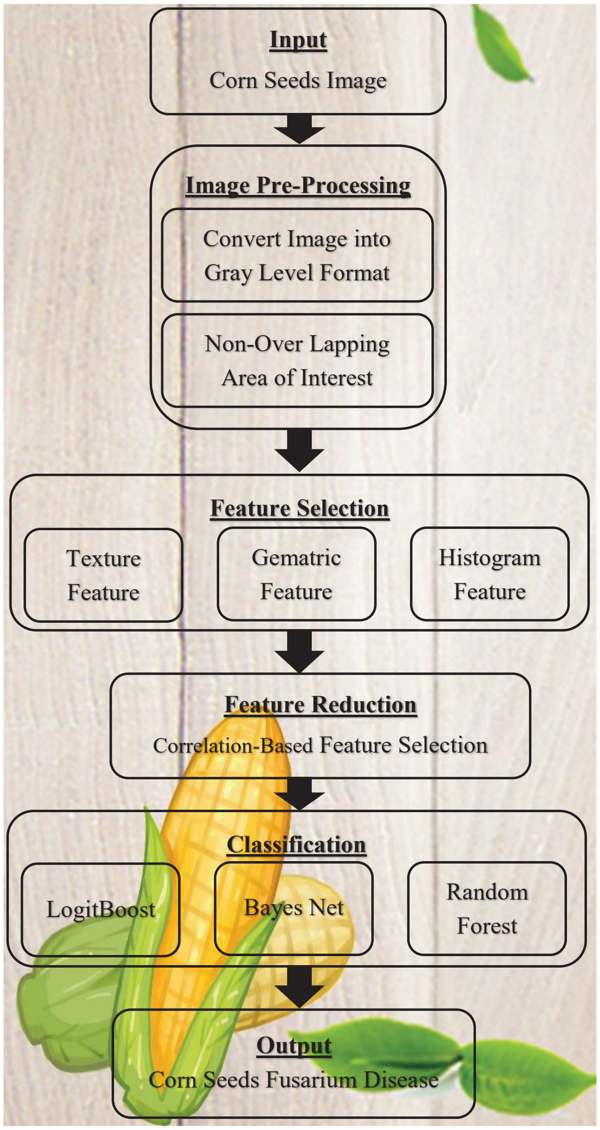

Fig. 3. Proposed Framework for his Study

types has been observed using the same strategy with same classifier, which is almost 96.67% to 97.78%. Among deployed classifiers namely LB, BN, RF, the LB shows the best accuracy result, which is 97.78%. The accuracy results of corn seed types on RF have been shown in Table 1.

The confusion matrix (CM) of the optimized multi-feature dataset is shown in Table 2. The accuracy results of six corn seed types, that is, Healthy, Fusarium Moniliforme, Fusarium Graminearum, Fusarium Gibberella, Fusarium Verticillioides, and Fusarium Kernel are 100%, 100%, 100%, 80%, 100% and 100% respectively. Graphically accurate results of six corn seed types using RF classifier have been shown in Figure 4.

A comparison graph of classification accuracy of six corn seed types using RF classifier on ROI's (200×200) has shown in Figure 4.

The classification accuracy results on ROI's (200×200) using BN classifier have been shown in Table 3.

The CM of the optimized multi-feature dataset has been shown in Table 4. The accuracy results of six corn seed types, that is, Healthy, Fusarium Moniliforme, Fusarium Graminearum, Fusarium Gibberella, Fusarium Verticillioides, and Fusarium Kernel are 100%, 90%, 100%, 100%, 93.33% and 100% respectively. Graphically accuracy results of six corn seed types using BN classifier have been shown in Figure 5.

A comparison graph of classification accuracy of six corn seed types using BN classifier on ROI's (200×200) has shown in Figure 4. The classification accuracy results on ROI's (200×200) using LB classifier have been shown in Table 5.

The CM of the optimized multi-feature dataset has been shown in Table 6. The LB classifier has shown best accuracy among all implemented classifiers. The accuracy results of six corn seed types is Healthy, Fusarium Moniliforme, Fusarium Graminearum, Fusarium Gibberella, Fusarium Verticillioides, and Fusarium Kernel are 96.66%, 100%, 100%, 90%, 100% and 100% respectively. Graphically accuracy results of six corn seed types using LB classifier have been shown in Figure 6.

A comparison graph of classification accuracy of six corn seed types using BN classifier on ROI's (200×200) has shown in Figure 7.

The overall classification result on ROI's size (200×200) using deployed classifiers namely RF, BN and LB have been shown respectively in Table 7.

Finally, the overall classification accuracy of employed classifiers, namely, LB, RF, and BN have been observed 97.78%, 97.22% and 96.67%, respectively shown in Table 7. It has been observed that employed classifiers, namely LB, RF, and BN, the LB classifier have shown excellent overall accuracy 97.78% as compared to other deployed

Table 1. Classification accuracy result of Random Forest classifier on ROI's (200×200).

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	Accuracy
Healthy	1.000	0.040	0.833	1.000	0.909	0.894	0.996	100%
Moniliforme	1.000	0.000	1.000	1.000	1.000	1.000	1.000	100%
Graminearum	1.000	0.000	1.000	1.000	1.000	1.000	1.000	100%
Gibberella	1.000	0.000	1.000	1.000	1.000	1.000	1.000	100%
Verticillioides	0.800	0.000	1.000	0.800	0.889	0.877	1.000	80%
Kernel	1.000	0.000	1.000	1.000	1.000	1.000	1.000	100%
Weighted Avg.	**0.967**	**0.007**	**0.972**	**0.967**	**0.966**	**0.962**	**0.999**	**96.6667%**

Table 2. Confusion matrix of Random Forest classifier on ROI's (200×200).

Classes	Healthy	Moniliforme	Graminearum	Gibberella	Verticillioides	Kernel	Testing Dataset	Training Dataset
Healthy	**30**	0	0	0	0	0	**30**	**70**
Moniliforme	0	**30**	0	0	0	0	**30**	**70**
Graminearum	0	0	**30**	0	0	0	**30**	**70**
Gibberella	0	0	0	**30**	0	0	**30**	**70**
Verticillioides	**6**	0	0	0	**24**	0	**30**	**70**
Kernel	0	0	0	0	0	**30**	**30**	**70**

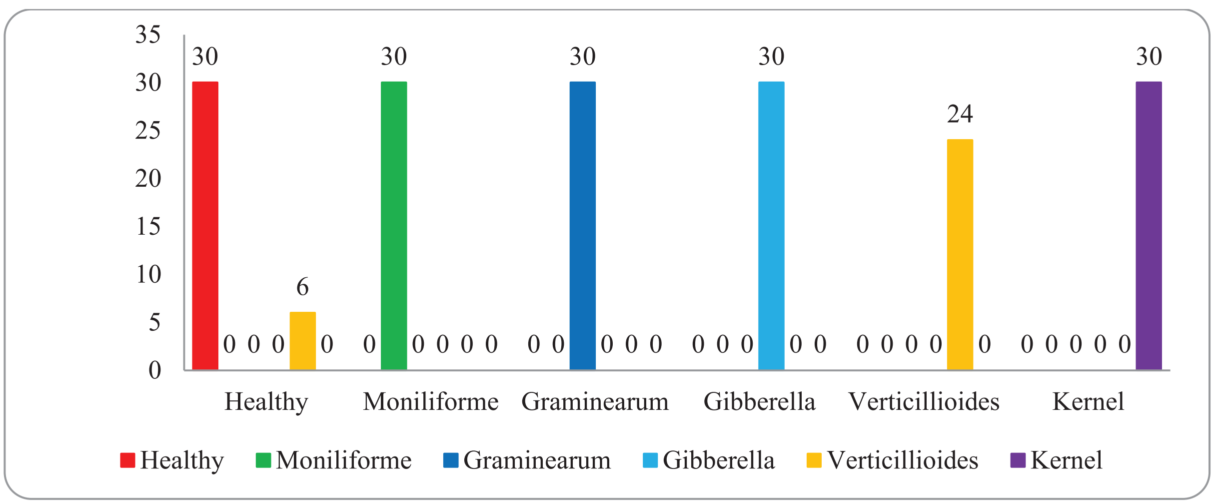

Fig. 4. Classification graph of corn seed types by using Random Forest classifier on ROI's (200×200).

Table 3. Classification accuracy result of BayesNet classifier on ROI's (200×200).

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	Accuracy
Healthy	1.000	0.013	0.938	1.000	0.968	0.962	1.000	100%
Moniliforme	0.900	0.000	1.000	0.900	0.947	0.939	1.000	90%
Graminearum	1.000	0.013	0.938	1.000	0.968	0.962	1.000	100%
Gibberella	1.000	0.007	0.968	1.000	0.984	0.980	1.000	100%
Verticillioides	0.933	0.000	1.000	0.933	0.966	0.960	1.000	93.33%
Kernel	1.000	0.000	1.000	1.000	1.000	1.000	1.000	100%
Weighted Avg.	**0.972**	**0.006**	**0.974**	**0.972**	**0.972**	**0.967**	**1.000**	**97.2222%**

Table 4. Confusion matrix of BayesNet classifier on ROI's (200×200).

Classes	Healthy	Moniliforme	Graminearum	Gibberella	Verticillioides	Kernel	Testing Dataset	Training Dataset
Healthy	**30**	0	0	0	0	0	30	70
Moniliforme	**1**	**27**	**2**	0	0	0	30	70
Graminearum	0	0	**30**	0	0	0	30	70
Gibberella	0	0	0	**30**	0	0	30	70
Verticillioides	**1**	0	0	**1**	**28**	0	30	70
Kernel	0	0	0	0	0	**30**	30	70

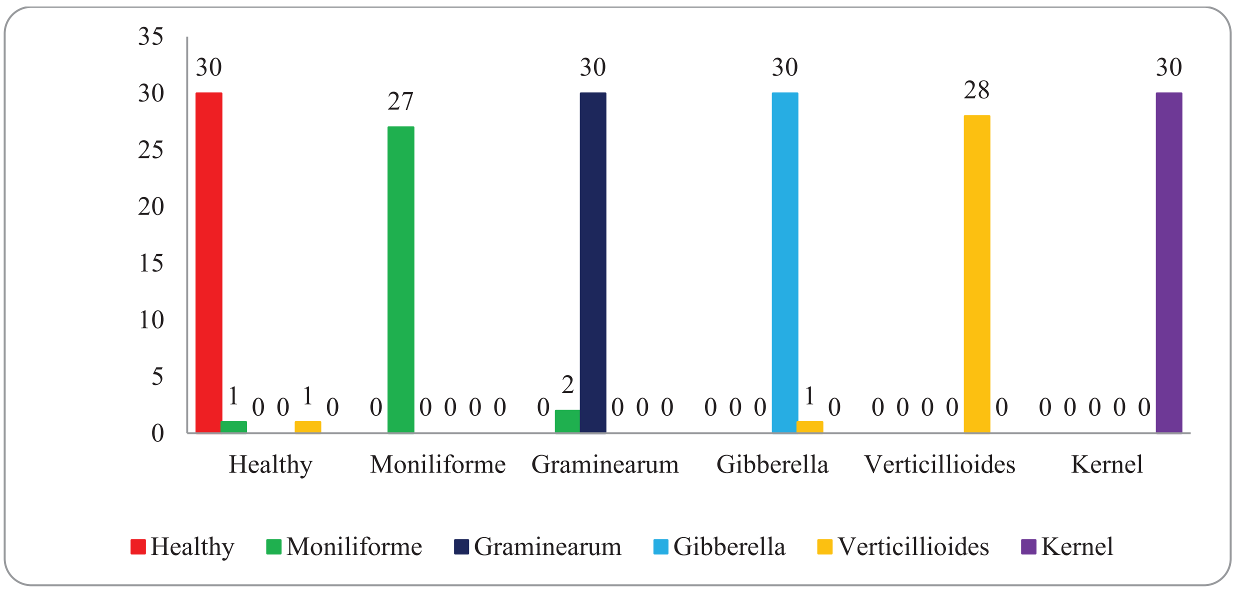

Fig. 5. Classification graph of corn seed types by using BayesNet classifier on ROI's (200×200).

Table 5. Classification accuracy result of LogitBoost classifier on ROI's (200×200).

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	Accuracy
Healthy	0.967	0.007	0.967	0.967	0.967	0.960	0.992	96.66%
Moniliforme	1.000	0.020	0.909	1.000	0.952	0.944	1.000	100%
Graminearum	1.000	0.000	1.000	1.000	1.000	1.000	1.000	100%
Gibberella	0.900	0.000	1.000	0.900	0.947	0.939	0.999	90%
Verticillioides	1.000	0.000	1.000	1.000	1.000	1.000	1.000	100%
Kernel	1.000	0.000	1.000	1.000	1.000	1.000	1.000	100%
Weighted Avg.	**0.978**	**0.004**	**0.979**	**0.978**	**0.978**	**0.974**	**0.999**	**97.7778%**

Table 6. Confusion matrix of LogitBoost Classifier on ROI's (200×200).

Classes	Healthy	Moniliforme	Graminearum	Gibberella	Verticillioides	Kernel	Testing Dataset	Training Dataset
Healthy	**29**	**1**	0	0	0	0	30	70
Moniliforme	0	**30**	0	0	0	0	30	70
Graminearum	0	0	**30**	0	0	0	30	70
Gibberella	**1**	**2**	0	**27**	0	0	30	70
Verticillioides	0	0	0	0	**30**	0	30	70
Kernel	0	0	0	0	0	**30**	30	70

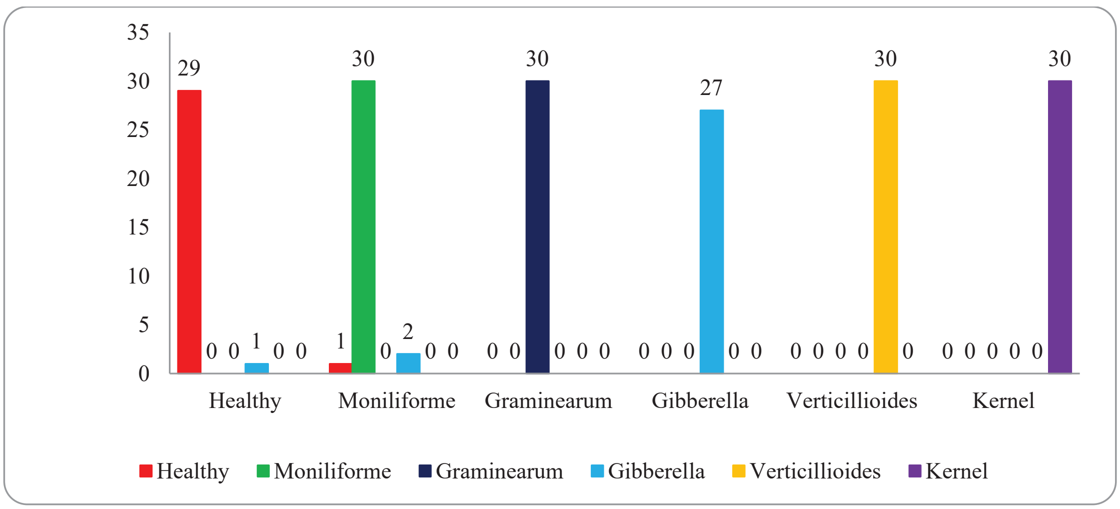

Fig. 6. Classification graph of corn seed types by using LogitBoost classifier on ROI's (200×200).

Table 7. Overall classification accuracy table for employed machine learning classifiers on ROI's (200×200).

Classifiers	Kappa Statistics	TP Rate	FP Rate	ROC	MAE	RMSE	Time (sec)	Obtain Accuracy
LogitBoost (LB)	0.9733	0.978	0.004	0.999	0.0284	0.0861	0.38	**97.78%**
BayesNet (BN)	0.9667	0.972	0.006	1.000	0.0097	0.0854	0.12	**97.22%**
Random Forest (RF)	0.96	0.967	0.007	0.999	0.0476	0.1179	0.48	**96.67%**

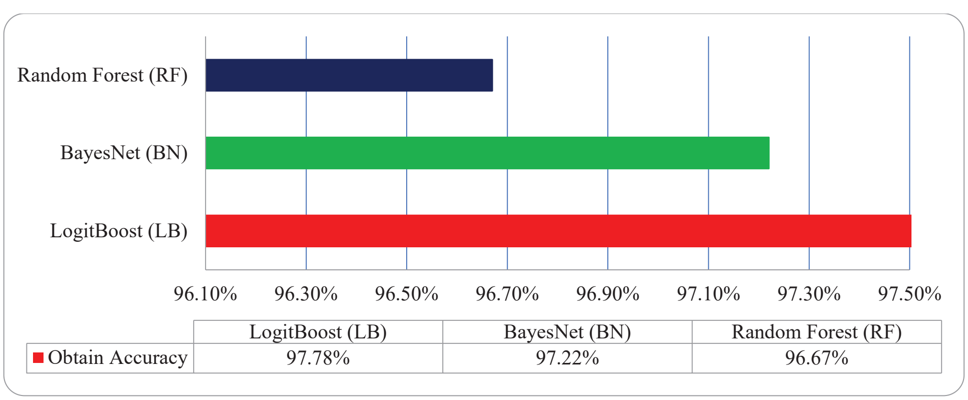

Fig. 7. Classification graph among three machine learning classifiers on ROI's (200×200).

classifiers as shown in Figure 7.

4. CONCLUSIONS

In this study, an automatic system has been introduced for the classification of corn seed Fusarium Diseases using multi-feature Space and Conventional Machine Learning Techniques. The main goal of this study selects most important feature using computer vision approach as well as selection of best classifier for obtaining efficient experimentation results. In this study we explore total six types of corn seed are collected which contain Infected Fusarium (moniliforme, graminearum, gibberella, verticillioides, kernel) as well as healthy corn seed. We face some fultuation due to envormental changes like sun ligth effects etc. The overall classification accuracy of employed classifiers, namely, LB, RF, and BN have been observed 97.78%, 97.22% and 96.67%, respectively.

5. ACKNOWLEDGMENT

The authors would like to thanks the three referees for their careful reading and for their comments, which significantly improved the paper. Additionally, thanks to Dr. Salman Qadri, (Assosiate Profassor, Chairman Department of Computer Science, MNS University of Agriculture, Multan) for his motivational support.

6. CONFLICT OF INTEREST

The authors declare no conflict of interest.

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