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A Survey of Seed Quality Analysis Using CNN

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Abstract
Grain is the primary crop that our country grows to increase agricultural income. The majority of grains on the planet are rice, wheat, and maize. These grains contain a number of impurities, such as stones, weed seeds, chaff, damaged seeds, etc. Grain quality assessment requires a big human workforce and low degrees of automation. It also lengthens and raises the cost of the testing procedure. As import and export trade grows, this conflict becomes more and more apparent. Grain handling techniques require a variety of grain varieties and their qualities before moving on to the next step. Digital image processing is a non-destructive method that is also very convenient and affordable, in contrast to the chemical approach. This paper presented a grain classification system based on machine learning and image processing algorithms to recognize quality of grains and assess the purity of grains. Techniques for image processing, segmentation, and feature extraction are used on the collected images and using the parameters like major axis length, minor axis length, area, and it also determines the purity of the grain.
***Keywords*: Agriculture, Classification, Convolution Neural Network, Prediction, Seed quality**

I. INTRODUCTION:

Agriculture has always been the backbone of the economy, and most jobs are still completed without the aid of contemporary technology. Currently, seed quality forecasting is done using human intelligence. The current analysis of seed prediction is not useful because it does not have a validation procedure. This study used to develop a prediction model that forecasts seed quality using machine learning algorithms in order to provide high crop yields and high-quality harvests. Convolutional neural networks were used to develop this model, which was trained using the seed dataset for accurate seed categorization. This model is used to determine if the seeds are premium quality, standard quality, or regular quality based on data that can be used to forecast the future. Training and validation data are used for classification purposes, whereas testing data are used in the algorithm's predictive analytics. The main objective of the project is to design the optimal technique for the more accurate prediction of seed quality by analysing the convolution neural network (CNN) model's training accuracy and the algorithm's prediction accuracy.

For a farmer, knowing the quality of the seeds is paramount. To get a good yield, the seed's quality is essential. Companies are usually the source of seeds for farmers. They'll make sure the seeds are of the highest calibre. But since they gather high-quality seeds by hand, there's a potential that they'll swap out high-quality seeds for damaged ones. Predicting the seed quality is the necessary precaution.

Our objective is to offer a method that will enable commercial farming to do away with the necessity of manual seed quality checks. Computer vision and deep learning algorithms are necessary for the autonomous identification of damaged and pure seeds. The suggested model makes use of a convolutional neural network to forecast the quality of the detected seed.

By employing the seed testing procedure to determine if a plant seed is flawed or not, this research study aims to intelligently improve the agricultural cultivation process. Finding seeds and assessing if they are defective are steps in the process of seed testing, which attempts to improve agricultural endeavours. This study tested the purity of different seeds using digital image processing technology. Digital image processing techniques are utilised to properly estimate the defect from the seed picture, in place of doing physical purity tests to determine the proportion of pure seed components in a seed batch. With recent advances in camera technology, anyone can readily snap digital images with a camera or a mobile phone device.

In the past 20 years, two non-critical testing techniques that have been widely used to predict the quality of food and agricultural goods are machine vision and near-infrared spectroscopy. These non-destructive methods are helpful because they promote the concurrent evaluation of physical and chemical data related to food without endangering the constituent. The primary benefit of these methods is their low cost and time consumption, which also have positive effects on food processing. As more precise and effective imaging technologies are developed, non-destructive methods appear to have a bright future in assessing the nutritional value of food and crops [4], [5].

The prediction algorithm is designed to assist individuals in upholding a verified process and framework when assessing the quality of seeds they wish to cultivate for commercial or scientific objectives in the agricultural sector. Because of the slow progress of technology, we remain underdeveloped in the modern world. People base their commercial practises and agricultural practises on wishful thinking and human intelligence. We now have the means to validate our expansion in terms of power, resources, capital, technology, mass production, and high-quality goods.

In addition to being a vital source of food for the human population, seeds are also employed as a starting point for the growth of crops. The quality of the seed has a major impact on crop yield, with environmental factors having a little impact. Predicting the germination of seeds is therefore a crucial and crucial undertaking. This is also necessary to assess the effectiveness of different seeds and enhance the efficiency of the food chain [6]. By 2050, the production of crops worldwide should have doubled to meet the demands of the expanding population [7].

Vigour is a highly significant factor that carries several implications when choosing high-quality seeds. The ability to use a seed's vigour to identify its qualities has been known about globally since the 1960s. However, because conventional techniques like the vigour test are laborious and time-consuming, their use has decreased as a result of the development of contemporary technologies like biotechnology, biophysics, seed image analysis, and molecular biology [8]. Furthermore, the majority of the seed tests created by the International Seed Testing Association are manual tests that vary from crop to crop and follow standardised procedures.

II. LITERATUREREVIEW:

The use of optical sensors in combination with machine learning methods has enabled advances in seed research. This work presents a novel approach to seed quality classification. Using techniques from X-ray imaging and Fourier transform near-infrared (FT-NIR) spectroscopy, classifier models were developed to predict the germination and vigour of seeds. The forage grass Urochaloabrizantha was selected as the model species. The FT-NIR spectroscopic data and radiographic images were obtained from single seeds, and the models were constructed using the techniques of support vector machine with radial basis (SVM-r) kernel, random forest (RF), naïve Bayes (NB), linear discriminant analysis (LDA), and partial least squares discriminant analysis (PLS-DA). Using FT-NIR and X-ray data, the models' respective accuracy for seed categorization (germination) was 82% and 90%. The models' accuracy for seed prediction (seed vigour) using FT-NIR and X-ray data was 61% and 68%, respectively. [9].

To understand the potential of multispectral imaging with various chemometrics algorithms in describing physicochemical quality attributes, forecasting physiological parameters, variety identification and classification, and detection of damages, defect, pest infestation, and seed health, a comprehensive study based on multispectral imaging applications for seed phenotyping and quality monitoring is conducted. Because of these incredible qualities, researchers have collaborated to develop fast, accurate, and reasonably priced spectral devices that will be utilised in the grain and seed industries. The capacity to gather three-dimensional data over a variety of electromagnetic spectrum wavelengths makes this feasible [10].

Based on the near-100% prediction accuracy for soybean viability, the FT-NIR spectral analysis research employing the PLS-DA approach, which takes into account all aspects or the selected variables, performed well. Both artificially aged and fertile soybean seeds are used in this investigation. PLS-DA was used to collect and analyse the FT-NIR spectra of soybean seeds in order to distinguish between viable and non-viable seeds. Furthermore, two approaches were utilised for variable selection: the variable significance in the projection (VIP) technique and the PLS-DA strategy [11].

A useful technique to assess the physiological condition of hybrid maize seeds and predict the sample's seed vigour is to combine chemometrics and attenuated total reflection Fourier transform infrared (ATR-FTIR) analysis. This paper also provides maize growers with a theoretical framework to optimise their genetics for greater physiological seed quality. The fast ageing of high-vigor seeds, which results in slight alterations in their biochemical composition under stress, illustrates the connection between the chemicals and seed vigour. Low-vigor seeds have a lower fat and protein content and a higher phosphorus, carbohydrate, and amino acid content, which makes them more sensitive to stress. Amino acid and phosphorus compound peaks are higher in high-vigor seeds [12].

Several types of seed samples and their application on individual plants were demonstrated using whole-seed samples from 240 different plants. This study employed the simple and reasonably priced ZX-50 NIR analysis of seed protein and oil content method. This method would be useful for soy breeding and research. The study's conclusions suggest that in order to generate predictions that can be relied upon, a suitable bias formulation should be developed beforehand using a range of cultivars with varying seed sizes and a wide range of variations in the objective attributes. When seeds that are distinct from those utilised by the producer to make the original product are included in the materials being investigated, it is extremely crucial [13].

A range of pre-processing and classification approaches were used to evaluate the vitality of rice seeds. To lessen the effect of differences in the spectrum data caused by factors including random noise, light scattering, and sample roughness, three pre-processing approaches were used. The spectral data was extracted using the hyperspectral image's regions-of-interest (ROI). The classification accuracy of the seed vitality of three different years was determined to be 87.5%, 93.33%, and 93.67%, respectively, using PLS-DA, least-squares support-vector machines (LS-SVM), and extreme learning machine (ELM). [14].

Five varieties of wheat seeds were examined and deployed using chemometric approaches and hyperspectral imaging technology in an attempt to classify them. Throughout the process, two exploratory methods for classification analysis—principal component analysis (PCA) and linear discriminant analysis (LDA)—were investigated indicate that, in comparison to models based on raw spectra data, the performance of three models based on different pre-treatment strategies did not significantly improve, indicating that pre-processing methods were not always successful in achieving classification recognition. [15].

This work focuses on a hyper spectral imaging system for short-wave infrared (SWIR) that was tuned and utilised to differentiate the viability of soybean seeds using near-infrared radiation (NIR). The equipment is useful for non-destructive viability measurement due to its bulk measurement capability and ease of integration with an automated seed separation process. Instead of identifying particular pixels in hyper spectral images, a kernel-based image processing technique was used in this work to classify the entire seed as viable or nonviable. The experimental results of this work show that the viability of soybean seeds can be predicted with 95% accuracy using the PLS-DA-VIP model, which was created using only a few wavebands [16].

A comparison of some of the key elements influencing the speed and precision of contemporary object detectors is carried out experimentally. The results of this study will enable practitioners to choose a workable approach for object detection in practical scenarios. This incorporates several cutting-edge tactics to boost speed without sacrificing accuracy, like employing noticeably fewer proposals than is customary for quicker R-CNN [17].

This study presents a number of augmentations that fall into one of two general categories: data warping or oversampling. These data-bending and oversampling search methods have a great deal of potential. The layered architecture of deep neural networks (DNNs) provides multiple options for data augmentation. Although most of the augmentations operate in the input layer and some are created from hidden layer representations, the output layer even makes use of the Disturb Label method. This cannot completely remove all bias present in a small dataset. Having access to large amounts of data usually reduces the issue of over fitting. [18]

A comprehensive image processing and machine learning pipeline was used to classify soil on different accessions of two kinds of Lucerne and red clover, as well as three stages of plant growth. Many approaches were compared in order to account for prior knowledge regarding the order in which the various stages of growth occur. With the help of a denoising technique that took into account the ontological order during the development stages, their proposed convolutional neural network-long short-term memory (CNN-LSTM) model achieved 90% detection accuracy19].

A predictive approach for classifying seeds using machine learning algorithms is being developed in an attempt to boost agricultural productivity. This study will use a machine learning technique to generate learning models that can identify patterns in data, create realistic simulations, anticipate the future, and classify incoming data. An artificial neural network (ANN) is used to model data and find patterns in complex relationships between inputs and outputs. This attempts to build models that predict machine-learning seed classes and understand the machine-learning process using neural networks. A seed dataset is used to evaluate the developed model, and seed classes are predicted using the developed model. Ultimately, the developed model is employed to determine and prioritise the factors influencing seed classifications [20].

Numerous physiological and morphological characteristics of the seed can be evaluated with greater thoroughness through the use of image analysis, which has several uses. It works by first using a captured image to extract numerical data, such as the colour, size, and shape of seeds and seedlings, and then processing that data with the right computer software. Compared to more conventional methods, image analysis has the advantage of rapid assessments, cost-effectiveness, automation, and an intuitive working environment. Image analysis systems have proven to be very helpful approaches for studies connected to seeds since they are more accurate, faster, and allow for intimate observation of seeds and sprouting seedlings [21].

The author emphasises how different features are used in the selected articles, taking into account the research topic and the data's accessibility. Each article looks at yield prediction with machine learning, however the features differ. Along with scale, geological location, and crop, each experiment is different. This study also points us that the models with the highest yield prediction performance were not always the ones with the most characteristics.. Neural networks, random forests, gradient-boosting trees, and linear regression are the most widely used models. Most of the research involved testing various machine-learning algorithms to see which produced the best predictions. This investigation indicates that the CNN, LSTM, and DNN algorithms are the most widely used deep learning algorithms [22].

To categorise weedy plants among the seeds, a study on seed classification was conducted. Both the seed datasets and the seed image were input. The seed image served as the input for the pre-processing stage. The ID3 method was used to compare a seed's characteristics to samples of other seeds in order to identify unwanted seeds. One explanation for low agricultural productivity is the use of poorly farmed soil. The data set of samples utilised in this study provides information about crop growth in soil, which facilitates the process of choosing the optimal soil for seeds [23].

It has been demonstrated that the interactive machine-learning method of identifying soybean seeds according to their appearance is highly accurate. This technique assigns vigour ratings to individual seedlings and effectively identifies damaged seeds. For classifying soybean seeds and seedlings, it is recommended to use the LDA, RF, and SVM algorithms based on data generated by the Ilastik programme. Soybean seeds with low physiological quality exhibit changes in fungal staining, mechanical damage, and chlorophyll degeneration [24].

CNN and transfer learning are utilised in the classification of faults in maize seedlings. Experiments are conducted to illustrate how well CNNs classify seed flaws. CNNs performed better than machine learning methods in assessing maize seed flaws, and the model's accuracy increased as the network's depth increased. The fault in the seed's appearance is one of the indicators used to assess its quality. While CNN can be applied to hyper spectral or multispectral images, it was only applied to RGB images in this study. The utilisation of multispectral images enhances the model's capacity for generalisation and application by permitting the identification of various types as well as the phenotypic characteristics of seeds [25].

This review examines research that shows machine vision's potential and ability to identify uneven rice grain samples with different sizes, shapes, and varietal types grown in different agro-environmental zones across the country using well-trained multilayer neural network classifiers. To classify the seeds, they used Weka classification techniques, such as the function, Bayes, Meta, and lazy approaches. They used the classifiers from these approaches: classifier multi-class, naive Bayes updateable, multilayer perceptron (MLP), sequential minimal optimisation (SMO), naive Bayes, and Bayes Net. This study suggests that three different cross-validation folds—10-fold, 5-fold, and 2-fold—as well as a training set approach can be used to categorise seeds. Through data analysis, researchers try to conclude that overall performance measurements decrease as the fold value decreases, with the exception of the MLP classifier, which uses 5-fold cross-validation to provide the highest accuracy score of 97.6%. [26].

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In order to select pepper seeds, the study uses a single predictor for each of the two variables (a* and single-kernel weight). This approach has advantages and disadvantages because it can lower selection rates while increasing germination rates. A single feature from each model was unable to simultaneously satisfy two essential needs: increasing the germination percentage and achieving a high selection rate. The aim of this work was to develop a binary logistic regression model for seed germination prediction. In order to determine the optimal selection approach, it also used the binary logistic regression network classifier. Binary logistic regression and MLP models were found to be more accurate in predicting the germination of pepper seeds than single-feature models. Comparisons of all the models revealed that the multilayer perceptron neural network, with 15 attributes chosen as covariates, was the best model. The germination rate rose from the initial 59.3% to 79.1%, the selection rate reached 90%, and the model stability was 99.4% [27].

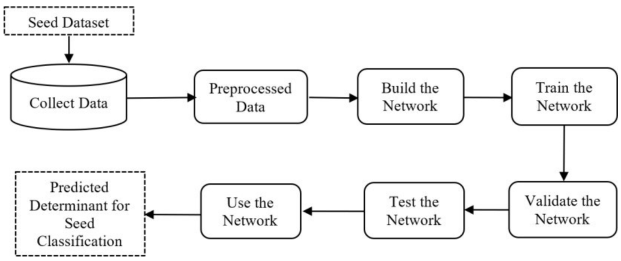
A demonstration that segments each maize utilising regional growth approaches employing 3D points from terrestrial Lidar scanning and deep learning is considered. 10,784 compressed images from 337 different samples of maize were used to train the quicker R-CNN to identify stems. Three sites at the same growth stage with different planting densities were used to test the stem recognition capacity. The proposed method is non-parametric and may be applied in a variety of field circumstances because the regional growth technique algorithm lacked parameters, which allowed the Faster R-CNN to identify the seed sites [28].

The scientists work on a thorough investigation into crop forecasting. Literary works state that a variety of machine-learning techniques have been employed to estimate agricultural production. Further research is done on root mean square error and other machine learning algorithm performance metrics. Along with machine learning methods, the impact of big data approaches on agricultural production prediction will be examined. A conceptual strategy is advised for the same. The recommended course of action is followed [29].

To evaluate many parameters and ascertain the quality of the soil, a framework was developed. The crops were recommended based on the information acquired throughout the mining process, depending on the outcome. More accurately and successfully, the method makes use of supervised machine learning to suggest suitable harvests. Although the system keeps track of the appropriate harvests based on the soil, the ranchers are still free to choose what crops to grow [30].

The literature review makes clear that there hasn't been much research done on seed quality prediction, and the results that have been found aren't good enough. Not many datasets are easily accessible. Thus, as part of our research, we generated our own datasets with three different categories—premium, standard, and regular—for bitter gourd, brinjal, and calabash seeds. In our research, we try to use machine learning approaches to analyse and forecast the seed quality.

III. FRAMEWORK FOR PREDICTING THE SEED QUALITY:



Frame work for predicting the seed quality

Rice:
Transgenic techniques have been used to characterize agricultural genes functionally, with model plants modified to contain desired gene coding regions or regulatory elements. Transgenic rice has been used to study genes contributing to drought resistance and other plant stressors. Gene editing, a modified version of the CRISPR methodology, has been effective in inactivating a rice gene controlling stomatal density, a crucial factor in water usage efficiency.

Wheat:
Transgenesis was initially used to study wheat genes, but rice was used in 1989 to uncover the functional components of a wheat gene controlled by the phytohormoneabscisic acid. The first transgenic viable wheat plants were reported in 1992. Transgenic approaches have shown interest in drought and heat tolerance in wheat, accounting for 10% and 2% of all documents, respectively.

Maize:
Transgenesis has been used to investigate maize genes by introducing them into dicots like tobacco and petunia and observing their expression. Maize is currently the most represented crop among genetically modified (GM) cultivars, with over 90% of approved events containing transgenes that shield plants from herbicide and insect stimuli. Since the first GM maize patent in 2000, several modified lines have shown greater tolerance to heat, salinity, drought, or non-native extreme weather (NUE). However, there is only one successful genetic engineering project that has produced commercial maize cultivars with increased resistance to abiotic stress.

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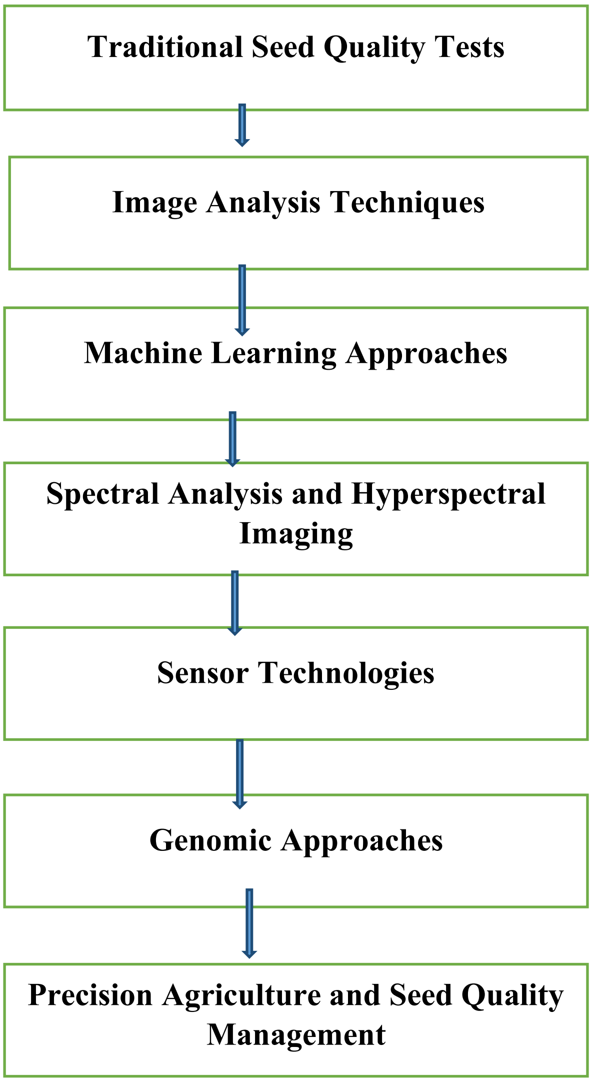
General Structure:



Traditional Seed Quality Tests:
Numerous studies have explored traditional seed quality tests for paddy, wheat, and maize, including germination tests, moisture content analysis, and purity checks. These methods serve as the baseline for evaluating seed viability and overall quality.

Image Analysis Techniques:
Image analysis has gained prominence in seed quality testing algorithms. Researchers have developed algorithms for analysing seed images to assess parameters such as size, shape, and color. This non-destructive method provides rapid and accurate results for seed quality evaluation.

Machine Learning Approaches:
Machine learning algorithms have been increasingly applied to seed quality testing. Studies have employed techniques like Support Vector Machines (SVM), Random Forest, and Neural Networks to classify seeds based on various quality parameters. These approaches offer the potential for automation and improved accuracy in seed assessment.

Spectral Analysis and Hyper spectral Imaging:
Spectral analysis and hyper spectral imaging have been explored for seed quality testing in paddy, wheat, and maize. Algorithms utilizing spectral data enable the identification of biochemical and physiological characteristics associated with seed quality, offering a non-invasive and rapid assessment method.

Sensor Technologies:
Advances in sensor technologies, including near-infrared spectroscopy and thermal imaging, have been integrated into seed quality testing algorithms. These sensors provide real-time data on seed properties, contributing to faster and more efficient quality evaluation.

Genomic Approaches:
Some literature discusses the integration of genomic information into seed quality assessment algorithms. Genetic markers associated with seed quality traits can be identified using molecular techniques, enhancing the precision of seed quality predictions.

IoT (Internet of Things) Applications:
The literature highlights the use of IoT in seed quality testing. Sensor nodes and data analytics in IoT frameworks enable continuous monitoring of seed storage conditions and facilitate timely intervention to maintain seed quality.

Challenges and Opportunities:
Challenges in implementing seed quality test algorithms include standardization, scalability, and the need for robust validation. Researchers also discuss opportunities for integrating multi-modal data, combining various technologies for a more comprehensive seed quality assessment.

Precision Agriculture and Seed Quality Management:
The application of seed quality testing algorithms in precision agriculture is a growing area of interest. Algorithms that integrate with farm management systems can contribute to optimizing seed usage, enhancing crop yield, and ensuring sustainable agricultural practices.
In conclusion, the literature review synthesizes diverse approaches to seed quality testing algorithms for paddy, wheat, and maize. The integration of traditional methods with cutting-edge technologies such as machine learning, imaging, and sensor technologies holds promise for advancing seed quality assessment in these crucial crops.

Different types of dataset for Rice, Wheat, Maize:
A dataset is an assortment of different kinds of digitally stored data. The foundation of any machine learning effort is data. Images, texts, audio, videos, numerical data points, and other types of media are the main components of datasets used to address different AI problems. Classification of images or videos.

Kaggle dataset
More than 40 photos of each agricultural crop are included in the dataset (Crop Images) (Maize, Wheat, rice). Over 159 enhanced photos of Crop photos of each class are included in the dataset (kag2). Horizontal flip, rotation, horizontal shift, and vertical shift are examples of augmentation.

Git Hub dataset
There are 124 distinct crop varieties are represented in the dataset. The dataset suggest that three most important crops are wheat (10106), rice (15082), and maize (13787).

Image Net dataset

Based on the WordNet hierarchy, 14,197,122 images have annotations in the ImageNet collection. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC), a benchmark for object recognition and image classification, has been using the dataset. There are a number of manually annotated training images in the publicly available dataset.

IV.RESULTS AND DISCUSSION

Once the model ran through 100 epochs with 30 steps each epoch, it was effectively trained. Ultimately able to achieve 97% training accuracy for the CNN Model. Predictive analytics has been used to anticipate the predictive score of the seed photographs in the testing dataset based on the training model. Once each image has been evaluated with a maximum predictive value under the selected category, the class position index number is used to predict the type and grade of seeds

. **Prediction accuracy**

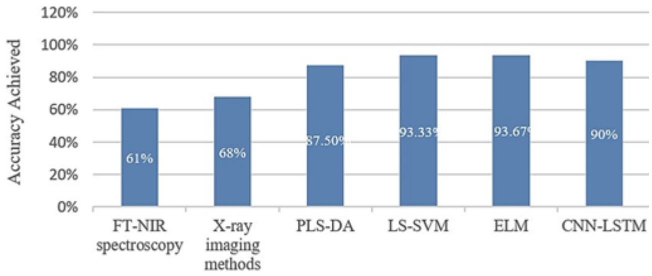
Seed Category	**Premium**	**Standard**	**Regular**
	0	0	0.5
	1	0	0.5
Rice	1	0.5	1
	1	0	1
	1	0	1
Wheat	1	0	0
	0	1	0.5
	1	1	0.5
Maize	1	1	0.5

Correct prediction-1;

Wrong prediction-0;

Partially correct prediction-0.5

Comparison of Different Methods and Techniques



Comparison of Different Methods and Techniques

Techniques used	**Accuracy achieved**
FT-NIR spectroscopy	61%
X-ray imaging methods	68%
PLS-DA	87.5%
LS-SVM	93.33%
ELM	93.67%
CNN-LSTM	90%

Seeds with the correct class and quality prediction are indicated as 1 (correct prediction=1); seeds with the correct class prediction but the incorrect quality prediction are indicated as 0.5 (partially correct prediction=0.5); and seeds with the incorrect class and quality prediction are indicated as 0 (incorrect prediction=0). Our manual calculation of the forecast accuracy using mathematical operations yielded a result of 64%, as indicated in Table 1. Table 2 and Figure 3 present the accuracy attained by the proposed technique and some of the existing methods, respectively. It is evident that the suggested method outperforms some of the existing methods.

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