Research Article

Survey of Seed Classification techniques

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ABSTRACT
Seed analysis and classification can provide additional information in the production of quality seeds. Generally, these activities are performed by specialists through visual inspection of samples of seeds. However, manual visual inspection of samples is a very tedious and time consuming task. Therefore, automation in seed analysis and classification is required. The work presented in this paper focuses on seed classification techniques useful for accurate classification of seeds. Different feature models, namely, color, texture-n-shape, shape-n-color, texture, and various combinations of the color, shape and texture were tested for the desired classification performances. Most of the feature extraction algorithms use the color, shape and texture features for classification. NNs have been used most of the time as they are universal functional approximators, are data driven self-adaptive, are nonlinear models, due to which are supple enough to model actual real world problems.With the help of experimental results, it has been confirmed that the individual features were showing the desired performance of seed classification near to the standards as prescribed by the International Seed Testing Association (ISTA).

Keywords: Color, Classification, Feature Extraction, Shape, Texture, Neural network.

1. Introduction and Motivation

A seed is the elementary and most acute input for sustainable agriculture. Further, the reaction of all other inputs in the field of agriculture depends on the quality of seeds to a large extent. For producing quality seeds, seed analysis and classification can provide additional information. This process is performed manually by specialists through visual inspection of samples of seeds. However, manual process is very tedious and time consuming. Therefore, automation in seed analysis and classification is required. The key feature of modern agriculture is high quality seed production because it has a strong connection to high quality crop production and linked costs.

Seed classification is a process in which different varieties of seeds are categorized into different classes on the basis of their morphological features. The branch of biology which deals with the study of the form and structure of organisms and their precise structural features is called Morphology. Labor-intensive identification of seeds is based upon conventional visual quality examinations performed by human beings, which may be monotonous, less efficient, time-consuming, slow, and inconsistent. The application of image processing is very significant in the agricultural industry, particularly in quality seed production. Now a days, computer vision and image processing algorithms are playing an important role in gaining quality production in a wide variety of fields to increase work efficiency. The work presented here involves quantification and classification of seeds using digital image processing and feature extraction while selecting quality seeds in agriculture.

1.1 Motivation

The costs associated with seed production and growth is about 20-25% of the overall production cost [1], which can be further raised up to 45% with efficient management of other inputs depending upon the crop [2]. Therefore, the classification of quality seeds and its development plays a significant role in the agriculture field. Today, getting quality seeds of a particular class is still a manual process or semiautomatic with partial image processing steps in many seed testing laboratories in India. However, as shown in Figure 1.1, there are many disadvantages of this manual seed analysis process and many challenges with the Computer Vision System (CVS).

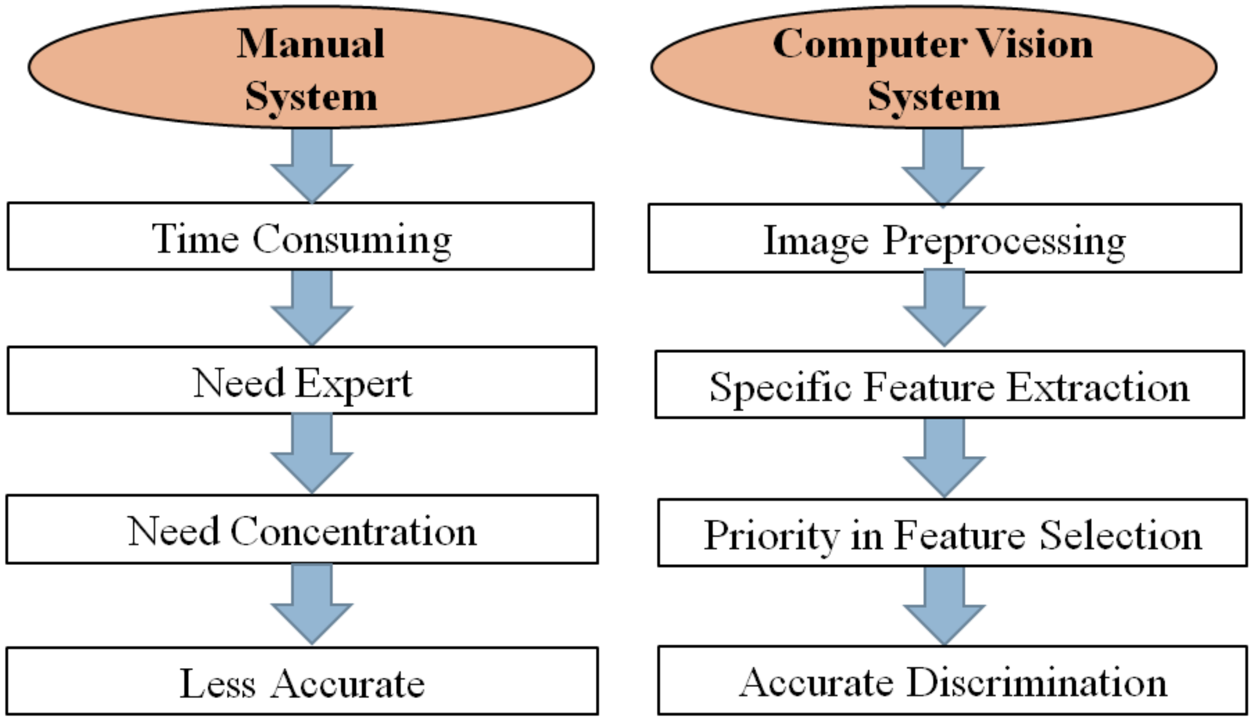

Figure 1.1: Disadvantages of Manual System and Challenges in Computer Vision System

i. Manual seed classification is time consuming as every sample seed needs to be inspected using Vernier Caliper or Photographic Enlarger. This leads to manual errors in classifying the quality of seeds in a specific class.
ii. Manual seed classification requires an expert capable of cleverly identifying similarities in the appearance of different species of seeds and variations in the same species of seeds.
iii. The evaluation process can be affected if the operator looses concentration after hours of working, affecting farmers in terms of returns for their crops.
iv. Image processing and feature extraction algorithms can be applied to the seed images to extract some quantitative information known as features of seeds. These features are then used as inputs to a classification algorithm to classify the seeds. There are plenty of colors, shape, and texture based features. However, the accuracy in selecting a specific class of seeds depends on feature selection and accuracy of the discriminator.
v. While capturing the seed images, seeds can be positioned in any arbitrary direction and at any position within the field of view. The features to be extracted may depend on the specific position of the seed. To capture a specific feature, seed images may have to properly preprocess.
vi. The images taken from the seed-lot may have seeds which are overlapped. In this situation either we have to separate out the seeds from the background or exclude the seeds altogether to avoid shape artifacts caused by overlap. Therefore, extracting the individual seeds and their features become another challenge for the image processing phase of the algorithm.
vii. It is quite possible that the seeds of a different variety (class) may be present in a particular sample of seed-lot with varying marginal difference in their feature characteristics. Identifying such a difference to get the correct seeds is also an important challenge.
viii. The Priority of extracting feature characteristics of the seeds may lead to a reduction in time required to classify the seeds. This will also decide the contribution of specific feature characteristics in the decision making process.
ix. Use of a proper discriminator in the decision making process plays an important role in deciding the accuracy of the classification of seeds, even in unbalanced classes of seeds within a specific group of quality seeds.

All the challenges mentioned above (i to ix) are really interesting. And efforts needed to overcome the problem associated with classification of seeds are not only dependent on innovation in feature extraction algorithms but also on the efficient use of technology and a multidisciplinary approach. Therefore, motivation lies in the application of innovation in exploring the Computer Vision System (CVS) for the benefit of farmers and society at large.

So far, the image processing algorithms with proper preprocessing and class dependent innovative feature extraction has not been applied to seed analysis by many researchers. With the ever increasing need of quality seeds in the Indian Agriculture field, motivation also comes naturally in developing a more efficient and economic way in the operation of the seed classification with the help of CVS.

1.2 Importance of Quality Seeds in Agriculture

Seeds, fertilizers, and pesticides are the three pillars of the modern agriculture system. The Green Revolution in India began with the introduction of the High Yielding Varieties (HYV) of seeds complemented by effective use of fertilizers and expansion of irrigation [3]. Seeds are the true carriers of technology. In India, three sets of institutions produce seeds: research institutions and agricultural universities; public sector seed producing corporations; and private sector firms, including multinationals.

Quality of soil and the type of seeds are two most important farming inputs. Better production in agriculture can be achieved only when seeds and soil are used wisely. For this it is essential to test the soil and seeds to come across the things that need to be added to optimize them. For this purpose, the government has set up a large number of testing laboratories for various types of seeds. The first determinant of the future plant development is seed. The seed is the master key to success with the cultivation methods. If good quality seeds are used, only then profits from breeding can be transferred to the farmer. The reasons for the need of various types of seeds are as follows:

1. Geographical locations in India experience different climates and hence the agricultural productivity changes from region to region.
2. India is extremely dependent on its monsoon cycle for large crop yields. Different regions in India have different soil and climate types, which are only suitable for definite types of farming.
3. Further, the germination and preliminary seedling growth in many tree species is often controlled by the specific class of seeds. Different types of seeds have diverse levels of starch and other food storage are a few factors that influence the germination and growth of the plants.

The sowing of the mixed seeds of a species can cause the formation of non uniform density of seedlings, which are heterogeneous in seedling size and vigor. Therefore, the compatibility of different varieties of seeds needs to be checked with local soil and other farming circumstances. The imported seeds are also tested for their aptness to Indian climatic conditions and tolerance to local diseases and pests. The most basic entity of agriculture is a seed, which govern the yield and quality of production. Good seeds make the investment on fertilizers, water, pesticides, and other inputs worthy.

1.2.1 Basic Components of Seeds

A seed is defined as a substance which is used for planting or regeneration purpose. A seed can be defined as a fertilized matured ovule, consisting of an embryonic plant, a store of food, and a protective seed coat as shown in Figure 1.2.

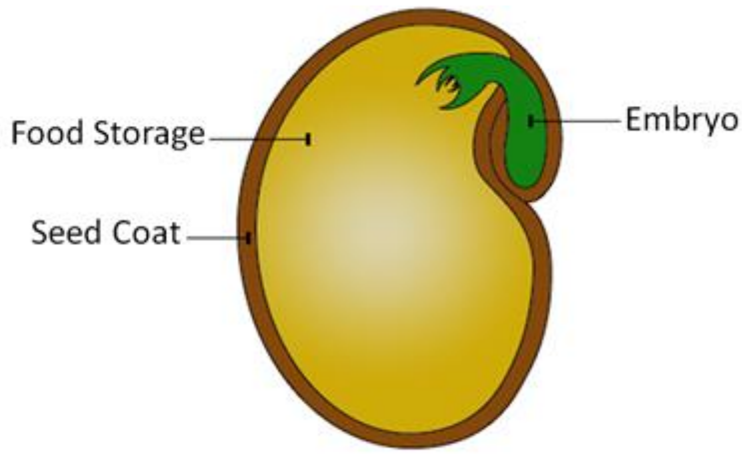

Figure 1.2: Seed and Basic Components of a Seed [4]

Based on the nature of the embryo, seeds are divided into two major classes called dicots and monocots as shown in Figure 1.3. Dicotyledon (Dicots) consist of plants with seeds that have two cotyledons and these plants are called dicotyledonous plants(e.g. Mango, Neem, Pea, Beans, Lentils, Peanuts, etc.;) On the other hand Monocotyledon (Monocots) consist of plants with seeds that have one cotyledon and these plants are called monocotyledonous plants(e.g. Grass, Sugarcane, Wheat, Rice, etc.).

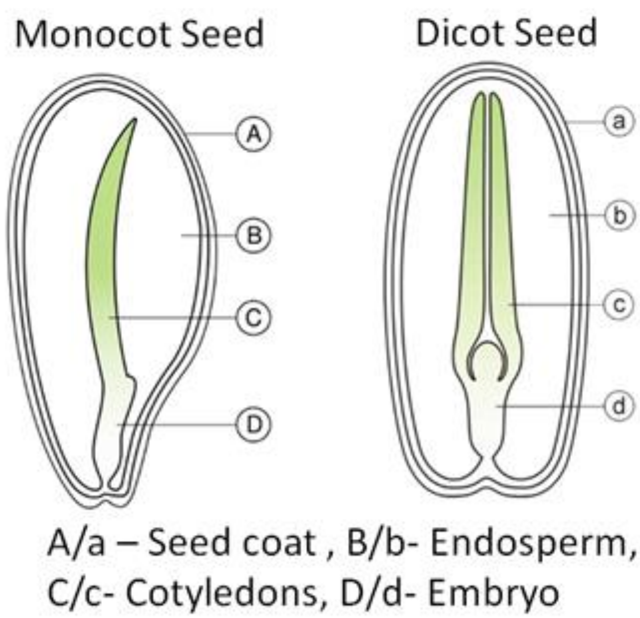

Figure 1.3: Monocot and Dicot Seed Structures [5]

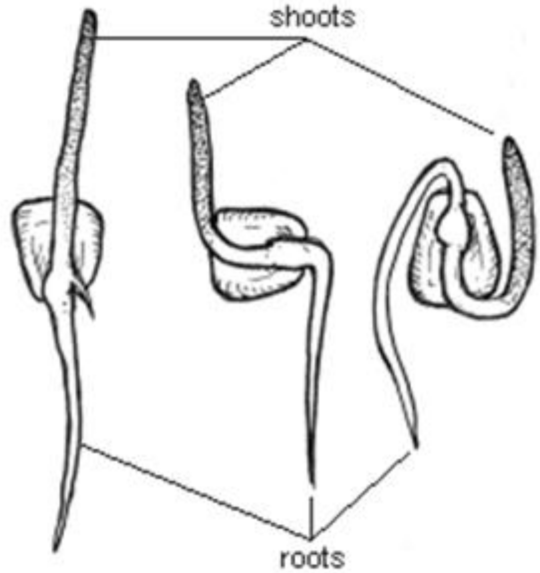

Figure 1.4: Shoots and Roots of the Seed Structures [6]

A store of food consists of cotyledons and the endosperm. In monocots, the endosperm serves as food storage tissue, whereas the cotyledon is important in food absorption. Upon germination, the cotyledons become the embryonic first leaves of a seedling. The number of cotyledons present is one of the characteristics that botanists use to classify plants. Species with one cotyledon are called Monocotyledonous or simply the Monocots, whereas species with two cotyledons are called Dicotyledonous or simply the Dicots, as shown in Figure 1.5.

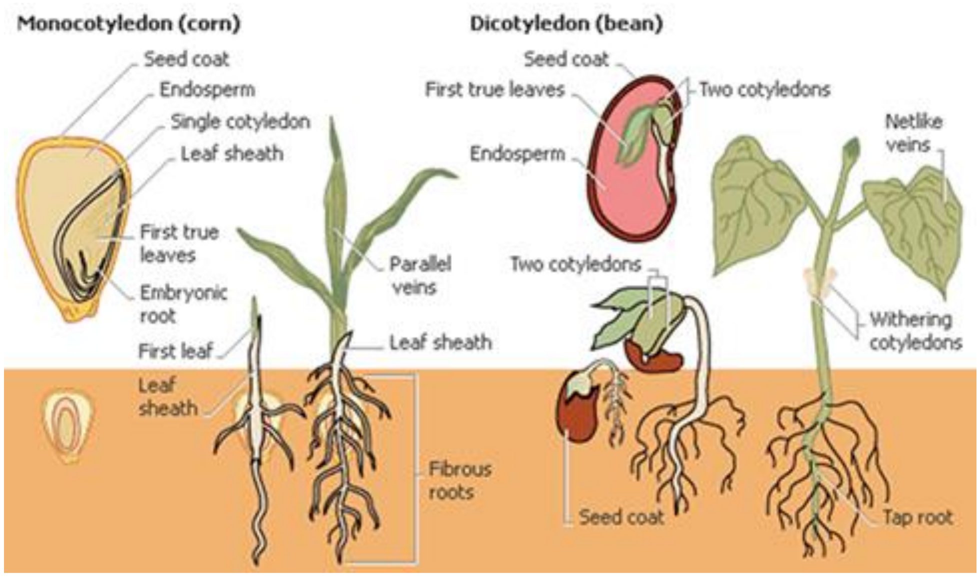

Figure 1.5: Seed and Basic Components of a Monocot and Dicot Seed [7]

1.2.2 Quality Seeds and Benefits

Seed quality is a relative term and can be defined as a degree of excellence when compared to an acceptable standard. Seeds that meet necessary standards of genetic purity, good health, physiological purity (viability and vigour), and other attributes are quality seeds.

Characteristics/attributes of quality seed are as follows:

i. Free from other crop seeds.
ii. Free from objectionable seeds in terms of size and shape.
iii. It should satisfy all the seed attributes for the specific class of seeds.
iv. Free from designated diseases.
v. High germination and vigour.
vi. Optimum moisture content.

Benefits of using quality seeds are as follows:
i. The good quality seed has high return per unit area as the genetic potentiality of the crop can be fully exploited.
ii. Less infestation of land with weed seed.
iii. Less disease and insect problem.
iv. Minimization of seed/seedling rate i.e., fast and uniform emergence of seedling.
v. Good seed prolongs life of a variety.
vi. High produce value and their marketability.
vii. It is estimated that good quality seeds can contribute about 20-25% increase in yield [8].

1.2.3 Existing Seed Testing for Quality

When considering the importance of quality seeds and benefits of using quality seeds, it is essential to test the seeds in seed testing laboratories and get certification. Seeds are tested in notified seed testing laboratories. At present, there are 107 seed testing laboratories in India and 7 in the state of Maharashtra [9]. Seed testing analyzes the parameters of seeds such as their germination capacity, physical purity, health, and admixture of other crop seeds based on the procedures prescribed by the International Seed Testing Associations (ISTA) and the Association of Official Seed Analysts (AOSA).

In this work,we considered the purity analysis. Each of the two major testing organizations, the ISTA and the AOSA, determine purity differently. ISTA rules specify a 3-part purity which reports percentages of pure seeds, other seeds, and inert materials, while AOSA rules specify a 4-part purity which reports percentages of pure seeds, weed seeds, other seeds, and inert materials[10].

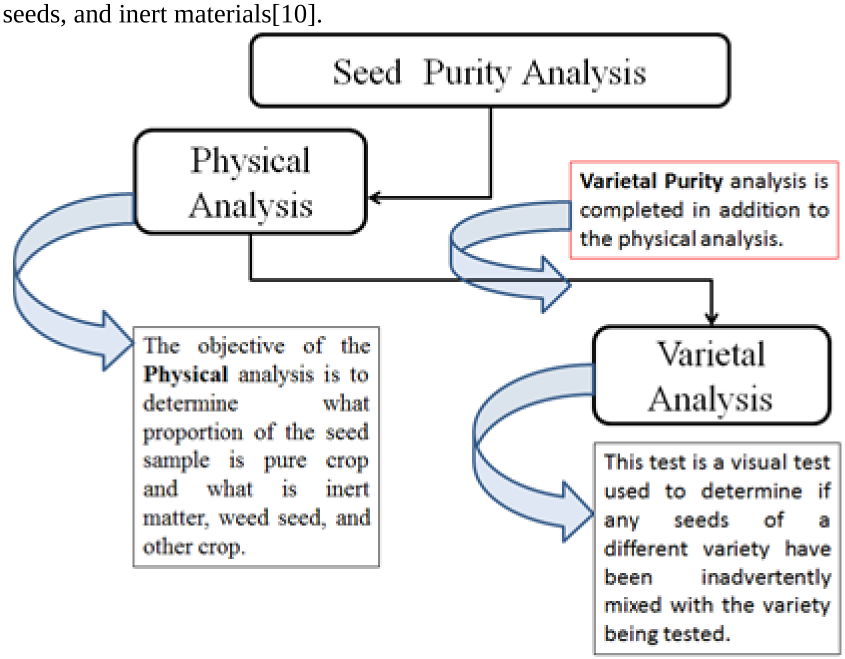

Figure 1.6: Seed Purity Analysis [11]

1. **Literature Review**

This section deals with seed testing fields and different feature extraction methods. It presents a literature review of existing seed classification work that relates to the research work presented in this thesis. The basic aim is to review different feature extraction techniques related to this work. The literature review is depicted with diagram showing number of papers identified per feature extraction and classification method. The analysis of previous work is discussed in the following section. The section ends with challenges and opportunities those are addressed in the thesis.

2.1 Seed Testing Fields

The testing fields can be categorized into two sections: Agriculture field and Computer Vision System fields.

2.1.1 Agriculture Field

A seed as an input is very important for agricultural production to increase. Seed testing is necessary to supply seeds of good quality, negate commixture in seeds, and become certified. Seed testing analyzes parameters of seeds such as: germination capacity, physical purity, health, and admixture of other crop seeds based on procedures prescribed by International Seed Testing Associations (ISTA). For the physical purity testing, normally one technician spends 80% of his service to perform this task. The classification method is not uniform even though the technicians receive similar training because it depends on their capability and personal circumstances. Problems like eye fatigue and call discrepancy between inspectors occur due to human participation throughout the test process. So, manual methods are unreliable and time-consuming for identification and classification of seeds. Therefore, to overcome these problems
automation is needed.

2.1.2 Computer Vision system

Image analysis results in classification of objects of interest and objects in the images. This process makes the evaluation of characteristics of visual quality in the agriculture domain easy. With the development of technology, computer vision systems are widely and reliably applied to identify agricultural products, and grade them by examining their quality. Computer vision has the potential to be used for seed health detection, detections due to insect and mite infestation, and classification and identification of damaged kernels. Therefore, the identification is reliable and fast. At this stage, the computer vision system is used to decide which extracted features are relevant for further processing. The potential of computer vision technology has been explored to discriminate between crops, weeds and background [12-14]. Image analysis using computers have previously been carried out for more than fifteen years in the agriculture domain to identify the varieties of the grain, categorize different grain varieties, identify impurities and evaluate grain health and seed purity [15-96].

2.2 Features of Quality Seeds and Classification

Image processing and feature extraction algorithms are applied to the images to extract some quantitative information known as features. The main aim of feature extraction is to translate the objects within an image into representations that depict their key features. Feature extraction is the process in which a pictorial representation of an image is translated to non pictorial. These non pictorial data representations of an image are called features and these features are identified and given for further processing. These features become inputs to a number of classification techniques for classifying the objects in the image. The feature vector is a compact representation of the objects within an image. It is an m X n dimensional array that encodes the m features of n objects within an image. The array contents are numerical (e.g., an integer expressing the length of an object, in pixels). A vector of such features is called a pattern. Pattern
recognition can be done by using the color, morphological and textural features, or a combination of these features.

Mere color features were applied for medicinal, castor, paddy, maize, rice, soyabean and wheat [15-22] classification purpose, the only shape features were comprehensively studied to non-destructively detect barley, wheat, rice, chickpea, weed, walnut and acacia [23-36]. Some researchers have merely tried texture features for classification of barley, wheat and weed [37-43].

To date, a bulk of grain tests using varied color and shape features involved the identification of barley, areca, wheat, corn, bean, cereals, Czech pea, cotton, soyabean, maize, lentil, Astragalus terraccianoi, and rice[44-61]. Likewise, the shape and texture were applied for bean, wheat, jatropha curcas, pollens, weed and rumex [62-68].

The color and texture were evaluated for corn, peanut, lentils and quiona [69-76]. And all the three color, shape and texture features have been integrated and applied for barley, soyabean, weed, cereals, pepper, rice, corn, and wheat [77-89]. Along with color, shape and texture features, wavelet was applied for cereal grain classification [90]. Grains samples assessment was done using spectra analysis [91].

Others included identification of rice based on GIST [92], SIFT[93], red clover based on physical [94], maize based on near-infrared spectroscopy and chemometrics [95], and others also included hough transform [96]. Figure 2.1 shows the Literature review w.r.t. features at a glance.

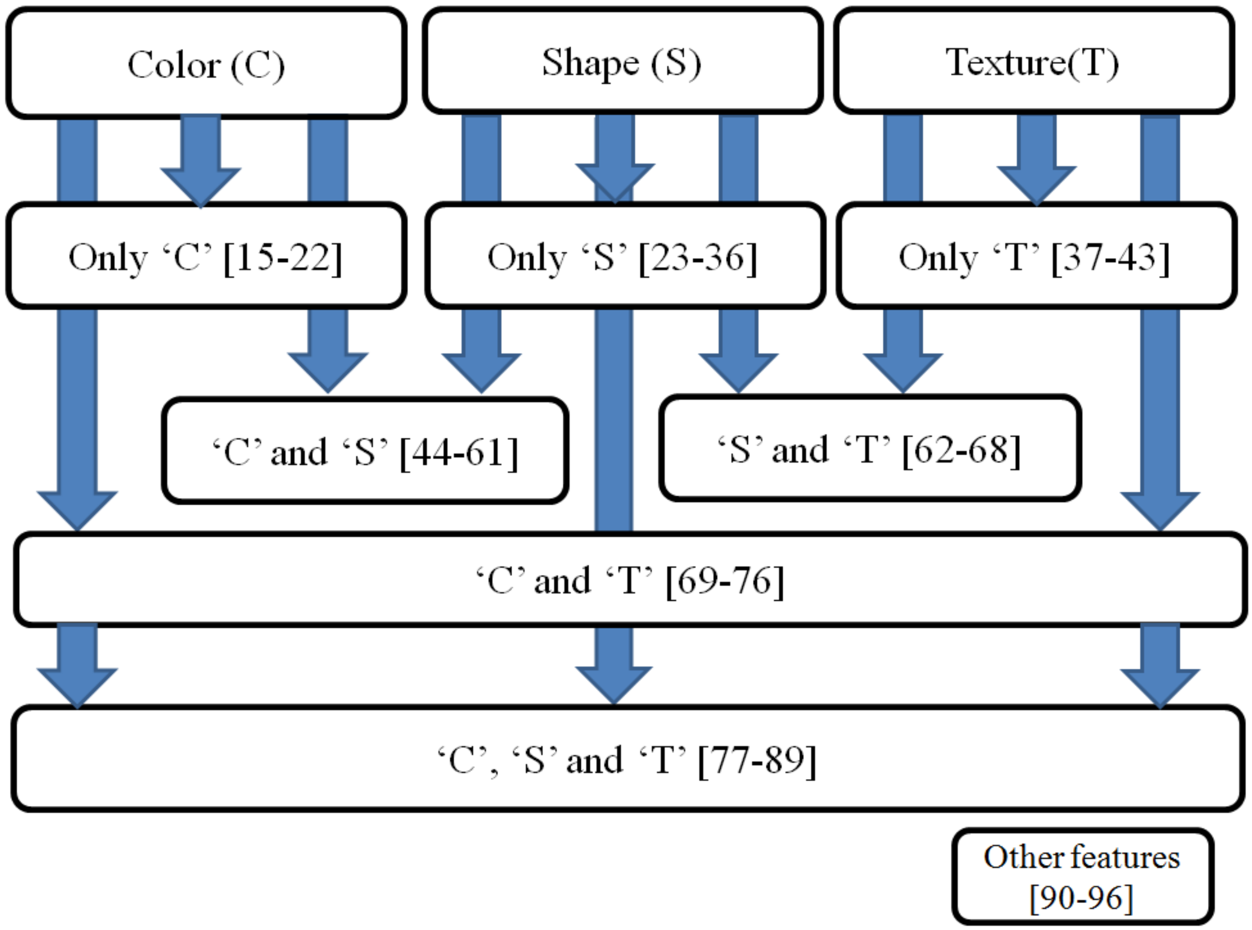

Figure 2.1: Literature review w.r.t. features

2.3 Literature review w.r.t features

Different features need to be extracted for proper classification of seeds. Different seeds have their own features which are extracted and given for further processing. Extensive work in feature extraction of seed, using image processing has been reported. They are categorized depending on different types of features. A large number of features have been extracted from color, shape and texture. Because the number of such studies is very large, only a small number

of related studies are briefly discussed in this section.

2.3.1 Classification of Seeds using Color, Shape and Texture (Basic) Features

Work based on mere Color, Shape and Texture Features are explained in this section, categorized as Classification using Color Features, Classification using Shape Features, and Classification using Texture Features.

a. Classification using Color Features

Sepideh Anvarkhah et al. [15] presented an automatic system for medicinal plant seed identification. Six color features (means of red, green and blue colors of the seed surface, as well as means of hue, intensity and saturation) were extracted by the algorithm and evaluated. Different combinations of color features (one, two three, four, five and six color features) were used. Results showed that the six color feature set showed the accuracy around 87.72% for testing.

Welma T. S. Vilar et al. [16] has demonstrated that using the color indices in RGB, HSI and Gray channels, castor seeds can be classified. The Partial Least Squares-Discriminant Analysis (PLS-DA) and linear discriminant analysis (LDA) were compared and it was found that the results given using PLS-DA were best; 97.5% to 98.8% .

A model was developed by Iman Golpour et al. [17] to identify five rice varieties using 36 color features. RGB, HSI and HSV Color models along with Back Propagation Neural Network (BPNN) was used to identify paddy, brown and white rice cultivars giving 93.3, 98.8, and 100 % accuracy respectively. From 36 features, 13 features were selected using STEPDISC analysis feature selection method giving highest accuracy as 96.66% . For testing data set the mean classification accuracy acquired was 98.8% with 36 features.

Cao Weishi et al. [18] presented maize purity identification by obtaining the 21 color features; RGB features of the seed crown, and then calculating separately the average of every band. Using BPNN as a classifier the identification accuracies were found to be 94.5% .

From the mixture of rice and sticky rice seeds the two were classified by Papol Punthumast et al. [19]. RGB color features were used as features for classification. The rule of classification between these two types was created. The rice seeds were accurately classified to almost 97.00% .

The color model RGB and HSI have been used by Xiaomei Yan et al. [20] for purity identification of maize seeds. The recognition done by K-means algorithm gave recognition rate as 93.75% .

Irfan S. Ahmad [21] developed a RGB color feature based multivariate decision model. Six color features comprising average, minimum, and variance for RGB values along with LDA was used for classification of soyabean. The 88% classification accuracy shows that color alone cannot adequately be used to describe the differences among symptoms.

M. R. Neuman et al. [22] examined mean of RGB; of different wheat classes using analysis of variance (ANOVA). It was found that wheat belonging to different classes are generally well-differentiated with R- and G-colour differences most evidently.

b. Classification using Shape Features

Invariant Elliptic Fourier Descriptors (IEFDs) have been used by Hibru K.Mebatsion et al. [23] to classify cereal grains. The classification was achieved using least square classifier and accuracies found were 99.7% for the first three IEFDs and 100% for the five IEFDs. H.K. Mebatsion et al. [24] analyzed the Fourier coefficient using PCA. The results discovered that the shape unevenness is represented by the PCA.

Piotr Zapotoczny et al. [25] determined the efficacy of features based on morphology for classifying five varieties of barley using seventy-four morphological features. LDA was found to be the best method amongst PCA, LDA, Non-linear Discriminant Analysis (NDA) giving accuracy around 94.94% . Using the Fishers coefficient, probability of error and average correlation coefficient feature selection methods, thirty features were selected from the seventy-four features.

This data reduction improved the results and it was concluded that the Artificial Neural Network (ANN) can be employed for the classification purpose.

B.P. Dubey et al. [26] employed 45 shape and size features to identify wheat varieties using ANN. The accuracy found was 88% . The results showed that the accuracy can be improved by the addition of more features like as color and texture.

Shape features such as area, compactness, major-minor axis, perimeter, aspect ratio, slender, spread, and five other shape factors, moments have been computed by S.P. Shouche et al. [27] for 15 Indian wheat varieties. Shape features were analyzed for 15 Indian wheat varieties using Euclidean distance. J. Paliwal et al. [28] evaluated nine different Neural Network (NN) architectures for classification of cereal grains. Eight morphological features like area, elongation, major-minor axis, perimeter, roundness, compactness and feret diameter were used to classify. The classification accuracies found were 88% to 97% . Amongst BPNN, General Regression (GRNN), Probabilistic Neural Network (PNN), Kohonen network; GRNN architecture was found to be the least appropriate for grain classification.

N. Sakai et al. [29] analyzed the shapes of brown and polished rice by measuring area, compactness, major-minor axis, perimeter, and elongation. After analysis, it was found that the area was correlated with perimeter, major-minor axis but not with elongation and compactness.

Accuracy ranging from 15-96% was found for classification of wheat cultivars.

M. Neuman et al. [30] determined Fourier descriptors and plan-form spatial shape features for classification. E. M. Kamel et al. [31] built up a system for identifying ten weed species and wheat grains based on the optimal set of morphological features. Four different classification algorithms namely K-Nearest Neighbours (K-NN), Naive Bayes, Quadratic Discriminant Analysis and BPNN classifiers were evaluated to select the effective one. Amongst the four classifiers, Quadratic Discriminant Analysis classifier reported the highest identification accuracy of 97.1% .

A new method has been proposed by Chetna V. Maheshwari et al. [32] for counting the rice long and small seeds. Then the rice seeds were quantified based on shape parameters. Salah Ghamari [33] compared the BPNN and Self-Organizing Map (SOM) ANNs for classification of chickpea seeds varieties, based on morphological properties of seeds. This study showed that SOM gave a better performance with 79% accuracy rather than BPNN with 73% accuracy. Adding color and texture can improve the performance of both ANN model.

S. Ercisli et al. [34] investigated 10 walnut cultivars developed in Turkey. Size and shape were the features used along with PCA and ANOVA. The PCA results were found attuned with the means of the walnut data compared with the ANOVA. The PCA showed that the projected area, equivalent diameter, perimeter, length, width, thickness, mass, volume, geometric mean diameter

and surface area were very important in distinguishing the walnut cultivars in terms of the dimensional and gravimetric features. It was concluded that all the cultivars were spherical and the highest values for shape factors were obtained from the horizontal orientation, followed by the suture and vertical orientations. V. Sivakumar et al. [35] revealed that the size and the shape both features were needed for identification of acacia species. Surface area, length, width, perimeter, roundness, aspect ratio and fullness ratio features were used along with 2D Discriminant analysis for discrimination of acacia species giving 96% accuracy.

Xian-Zhong Han et al. [36] discussed the feature value of wheat seeds and calculated the comprehensive evaluation by AHP. To build the model the features extracted were shape features, such as area, rectangular, plumpness, and elongation. Experiments showed the accuracy rate is more than 95% .

c. Classification using Texture Features

Smooth and wrinkled regions were identified by Piotr M. et al. [37] to analyze barley kernel. The orientation, crease visibility, and germ location were also described. This gave an accuracy of 93% .

Alireza Pourreza et al. [38] applied machine vision techniques to classify nine common Iranian wheat seeds based on their varieties. 131 textural features, including 32 gray level textural features, 31 Local Binary Pattern (LBP) features, 31 Local Similarity Pattern (LSP) (μ, σ, smoothness, 3rd moment, uniformity, entropy, gray level range and 25 histogram groups for each gray level, LBP and LSP features), 15 LSN features (histogram of LSN matrix containing nine features), 10 Gray-Level Co-occurence Matrix (GLCM) features (μ, var., entropy,uniformity, homogeneity, inertia, cluster shade and prominence, max. probability and correlation). 12 Gray-Level Run Length (GLRL) features (short, long run, gray level and run-length non-uniformity, run ratio, entropy, low gray and high gray level run, short run low and short run high gray level, long-run low and long run high gray level) were extracted. LDA classifier was employed for classification using top selected features. The average classification accuracies found were 98.15% .

Eight western Canadian wheat varieties were identified by A. Manickavasagan et al. [39]. 32 texture features along with quadratic and LDA classifiers were adopted giving an accuracy of 89.8% and 85.4% respectively.

Determining the potential of Wavelet texture features for classification of eight wheat species, using linear and quadratic statistical pattern recognition technique and BPNN, has been the primary focus of R. Choudhary et al. [40].

Energy and entropy features at each level in the horizontal, vertical, and diagonal orientations were amongst the extracted features. The contribution of energy was found to be more than the entropy features. Features at finer resolutions were found more important than features at coarser resolutions. With top 90 features, the highest average classification found was 99.1% with LDA.

Three different illuminations were tested to find their efficiency to identify eight western wheat species by A. Manickavasagan et al. [41]. LDA along with 32 gray level texture features was investigated. Amongst the three illuminations i.e. incandescent light (IL), fluorescent ring light (FRL), fluorescent tube light (FTL), FTL generated higher accuracy as 98.5-100 % .

Piotr Zapotoczny [42] examined eleven varieties of wheat using the image histogram, GLRL, GLCM, wavelet transform and the AR model texture features for seven channels. LDA and ANN were tested for classification. Classification accuracy found was 100% with texture features and ANN. T.F.Burks et al. [43] evaluated three classifiers based on Neural Network for classification of weed using Color Co-occurrence Method (CCM) texture analysis. After the comparison of BPNN, counter propagation, and radial basis classifiers, it was found that BPNN provided the highest performance of 96.7% accuracy.

2.3.2 Classification of Seeds using Combination of Features

Work based on combination of Color, Shape and Texture Features are explained in this section categorized as Classification using Color and Shape Features, Classification using Shape and Texture Features, Classification using Color and Texture Features, Classification using Color,Shape and Texture Features and Classification using other features.

a. Classification using Color and Shape Features

A maximum classification accuracy of 98.5-100% was achieved for individual variety of grains using combined color and morphological features by H.K. Mebatsion et al. [44]. The other feature models apart from combined color and morphological features were only color, morphological, EFD, Symmetric Fourier Index (SFX) and Invariance Index (IFX). The morphological features included Fourier index, major diameter, aspect-ratio, and roundness and color features included color indices of RGB values.

Kuo-Yi Huang [45] achieved a classification accuracy of 90.9% to classify areca nuts using ANN and color and shape features. Along with defects area, three color features including μ of RGB, and six geometric features including major-minor axis, axis ratio, centroid, area, perimeter, and compactness were used.

Marian Wiwart et al. [46] proposed a model based on color and shape for identifying hybrids of spelt and wheat using PCA. The color features used were HSI and LAB. The shape features used were the area, perimeter, circularity, feret, minimal feret diameter, aspect ratio, roundness and solidity. With shape descriptors, the percentage of variation achieved was 98.98% and with color was 90.27% .

The accuracy achieved by Xiao Chen et al. [47], for classification of five corn varieties was 90% . A total of 58 features which included 30 morphological and 28 color features were extracted. From the μ and σ , of R,G,B, r,g,b, Y,Cb,Cr, I1,I2,I3, H and S color features, six color features (μ of r,g and σ of r,g, I1) were selected using stepwise discriminant. A two-stage classifier combining the Mahalanobis distance analysis and the BPNN was developed for classifying the corn varieties. Gianfranco Venora et al. [48] measured color and shape features of Italian landraces of the bean. Statistical analysis was done using LDA giving the accuracy 82.40 to 100% .

A method was developed by Kivan Kilic et al. [49] for inspecting beans based on color and shape features. The color features used were μ, var., skewness, and kurtosis for RGB model and the shape features used were length and width. The classification rate achieved was 90.6% .

N. S. Visen et al. [50] compared four simple and specialist neural network architectures namely BPNN, Ward network (WN), GRNN, PNN for handling classification of cereal grains. Four color features (μ, σ, median and mode of gray-level) and eight morphological features (area, perimeter, major-minor axis, elongation, roundness, feret diameter and compactness) were applied as input to ANN. The specialist PNN gave the best accuracy around 96.7-98.7% .

Smykalova et al. [51] implemented classifier to be able to discriminate five varieties of Czech pea. A total of 33 color, size and shape features of seeds of five Czech pea varieties, were extracted to identify and discriminate between the varieties. Statistical analysis were performed with LDA. The overall accuracy achieved was 70.0% for training and 69.12% for testing sample sets. Individual variety identification achieved was between 53.8% to 98% .

Alireza Pazoki et al. [52] has demonstrated that using the Multi-Layer Perceptron (MLP) can result in 94% and using Neuro-Fuzzy neural networks can result in 96% accuracy for classifying corn varieties using 12 color and 15 morphological features.

Li Jingbin et al. [53] proposed a nonlinear identification method based on BPNN and investigated three varieties of delinted cottonseeds. 12 color features including μ and σ of R,G,B, H ,S and I, and 14 shape features including area, perimeter, NCI ratio, circular degree, centroid, major-minor axis, 2nd moment (X,Y,XY) , major-minor axis of oval, shape coeficient of oval were extracted.

Also, comparison between BPNN and step discrimination analysis method was done. It was found that BPNN identification method gave higher accuracy than the step discrimination method and the test accuracy rate was 90% .

Jiang Jingtao et al. [54] introduced Split Bregman method which had closed continuous border and high accuracy of feature extraction. To solve optimality conditions of bregman split method the collocation method was employed. Using SVM classifier results showed the identification accuracy 97.3% - 98% .

Rafael Namias et al. [55] showed that morphological features have low discrimination capabilities for soyabean and that a set of color features provide good separation among soyabean grades. 38 features (10 morphological, 28 color) along with RF and SVM classifiers were used for discrimination. The average accuracy for morphological features found was 56% for RF and 59% for SVM, for color was 78% for RF and 77% for SVM. The average accuracy for both combined features found was 77% for RF and 78% for SVM.

Four wheat varieties were correctly identified by Arefi et al. [56] by using ANN based on color and morphology. Mean, variance, skewness and kurtosis of RGB and LAB color models were extracted for the color features and area and 4 shape factors for the shape feature giving total eleven features. 280 images were used for training, 40 for validation and 80 for testing giving overall classification rate as 95.86% .

Miroljub Mladenov et al. [57] used 11 color and 4 shape classes to test the accuracy of maize recognition. Specific Classifier Architectures, based on Radial Basis Elements (RBEs) were used for recognition. For color features accuracy found was 90% and in the case of shape recognition, it was 73% when the impurities were removed from the testing sets.

Five lentil cultivars were correctly identified by Shahin and Symons [58] with a correct overall performance of 98.93% for training and 98.87% for testing set. Two features -seed area and hue- along with the rule-based classifier identified all the five varieties with an overall accuracy approaching 99% .

Gianluigi Bacchetta et al. [59] identified Sardinian species using color and shape features. The seed size (area, perimeter and diameter of the seed projection), shape (shape, roundness and circular geometrical descriptors of the seed projection), and color (red, green, blue, hue, lightness and saturation values of the seed surface pixels and their relative dispersion values) and density were measured. Data were statistically analyzed using the stepwise LDA giving the
inter-population accuracy as 92.5% .

Liu, X et al. [60] extracted 18 color features; sum, μ, σ for RGB and HIS color models and 12 shape features; contour point number, circumference, area, major-minor axis length, maximum and minimum circle radius, largest span, elongation, equi. diamtr, roundness, and compact ratio for maize seed varieties identification giving identification accuracy more than 95% .

Liu Zhao-yan et al. [61] designed an algorithm based on seven color and fourteen shape features for the identification of six paddy varieties. μ of RGB and HSI and σ of H were among the seven color features. Area calculated by calibration factor, length, width, major-minor axis length, thinness ratio, aspect ratio, rectangular aspect ratio, equivalent diameter, filled area, area, convex
area, solidity, and extent were among the fourteen shape features. Seven color and fourteen shape features along with ANN gave accuracy around 74-95% .

b. Classification using Shape and Texture Features

Marisol Lo Bianco et al. [62] measured overall of 138 size, shape and texture descriptors to identify 67 Italian bean accessions by applying the LDA giving overall correct identification percentage higher than 88% .

Studying eight morphological and five textural properties of hard red and white wheat varieties was the main purpose of Stephen R. Delwiche et al. [63].

LDA and K-NN were tested for recognition of kernel damage. The morphological features used in classification included area, projected volume, perimeter,ellipse eccentricity, and major and minor axis lengths. Textural features from calculated GLCM included contrast, correlation, energy, homogeneity and entropy and elliptic Fourier descriptors. Combination of two morphological and four texture properties attained 91 to 94% classification accuracy.

Junfeng Gao et al. [64] investigated a technique to distinguish the topographical source of Jatropha curcas L. seeds.7 morphological features of samples comprising area, perimeter, extent, eccentricity, major-minor axis length and the circularity ratio and 5 GLCM textural features comprising contrast, homogeneity, energy, correlation and entropy for 0 were figured and utilized for LS-SVM classification giving the accuracy of 93.75% .

Maria et al. [65] detected pollen grains on a slice by processing the shape and texture features. The closed outline of every grain was detected utilizing the three methodologies, namely, edge, snake, and convex-hull-contour. A number of shape features, to be specific, geometrical features, Fourier descriptors and statistical moments were extracted. Four different texture techniques; namely; First-order, GLCM, GLRL and Neighboring Gray Level Dependence Statistics were also used. For the classification three different classifiers; Minimum Distance Classifier (MDC), MLP and SVM were tested. The MDC classifier consolidated with the feature selector FSM is observed to be better than the SVM classifier and the MLP classifier. The classification accuracy accomplished was 89% .

P.M. Granitto et al. [66] discussed the likelihood of enhancing the naive Bayes and ANN classifiers already created in their previous research keeping in mind to dodge the use of color features as classification parameters for classifying 57 weed species. It was concluded that boosting the naive Bayes and ANN does not fully recompense the discriminating power of color features.

Adjemout ouiza et al. [67] carried out the recognition using the nearest Euclidean distance on the basis of shape and texture features. 15 shape features namely perimeter, surface, circularity, major-minor axis, moments were computed from the pre-processed images. Texture features namely spatial gray-level dependence (GLD) method were additionally used. The recognition rate based on shape features found was 85.75% and on texture features found was 78% . The combination of these features enhanced the recognition up to 89.25% .

Younes Chtioui et al. [68] identified four seed varieties by comparing stepwise discriminant analysis and ANN using the blend of shape and texture features. The seed varieties included two crop species, lucerne and vetch, which was contaminated by the two weed species, rumex and wild oat. The ANN outperformed the discriminant analysis giving the accuracy as 92 to 99 % .

c. Classification using Color and Texture Features

Xiaoling Yang et al. [69] built up a novel system for the characterization of corn seed assortments taking into account shape and texture. Five shape features comprising area, circularity, aspect ratio, roundness, and solidity and eight texture features comprising of energy, contrast, correlation, entropy, and σ were extracted. SVM and a PLS-DA model were utilized to build the classification models. The recognition accuracy accomplished by the SVM model was more acceptable than by the PLS-DA model. The accuracy found was 98.2% for germ side and 96.3% for endosperm side.

Kuo-Yi Huang [70] detected and classified Phalaenopsis seedling ailments including Bacterial Soft Rot (BSR), Bacterial Brown Spot (BBS), and Phytophthora Black Rot (PBR). GLCM was utilized to assess the texture features (contrast, uniformity, maximum probability, homogeneity, inverse difference, difference variance, diagonal variance, entropy, and difference entropy of G and B bands of the lesion area), and three color features (the mean gray level of lesion area on the R, G, and B bands) were utilized as a part of the classification methodology. BPNN was employed for classification giving accuracy around 89.6% .

BPNN was employed by Han Zhong-zhi et al. [71] for quality grade testing and identification of peanut kernels with 95.6% accuracy. 52 features based on color, form and texture were employed for identifying peanuts.

Lentils were graded by M.A. Shahin and S.J. Symons [72] using color and texture features. 25 color and texture features were selected by Wilks Lambda. Three different classification models LDA, K-NN, and NN were developed. Testing with LDA achieved 91% accuracy, with NPAR achieved 88% and with NN achieved 90% .

Dayanand Savakar [73] classified eight different types of food grains. 18 color and 27 texture features were extracted and classification was done using a BPNN. Individual color, texture and combination of both color and texture features were used. The combination of features beat the performance of individual color and texture features. The color features did not exceed 87% texture features did not exceed 84% , and the combination gave 85-92% accuracy for identification of individual varieties.

Kantip Kiratiratanapruk and Wasin Sinthupinyo [74] proposed a technique using SVM for classifying more than ten types of corn seed defects by utilizing color and texture features. Color histograms in the RGB and HSV color space and texture features such as energy, contrast, correlation and homogeneity based on GLCM and LBP for classification were adopted. The obtained accuracies were 76% and 56% for color and texture features respectively whereas 81.8% for the combination of both color and texture.

W. Medina et al. [75] recognized land provenance of 25 varieties of quinoa seeds, from 38 averaged measurements as geometric and fractal dimensions and morphological and color features. PCA and hierarchical cluster analysis helped in distinguishing five varieties cultivated in Europe.

N.S.Visen et al. [76] identified the grain type using 123 color and 56 textural features and a BPNN classifier. Five different sets were created using the different combinations of features. The classification accuracies obtained utilizing different input feature sets for all grain types were 98% . Best results achieved were using the mixture of both color and textural features.

d. Classification using Color, Shape, and Texture Features

Piotr M. Szczypinski et al. [77] assessed the adequacy of identifying barley varieties based on 295 color, shape and texture features. Varieties were identified by reducing feature space dimensionality and using linear classifier ensembles and ANN. The output produced by the NN classifier was 67 to 86% accurate when contrasted with the linear classifier ensemble which gave the accuracy around 40 to 65% kernels. The study exhibited that classification results can be essentially enhanced by standardizing individual kernel images in terms of their anteroposterior and dorsoventral orientation and performing additional analysis of wrinkled areas.

Dejun Liu et al. [78] identified damaged soybean seeds by using three color (mean value, standard deviation and MDCD value of L*a*b), eight shape (perimeter, area, circularity, elongation, compactness, elliptic axle ratio, equivalent diameter) and three texture features (energy, contrast and entropy), as an input to BPNN. The average accuracy achieved was 97.25%.

Pablo M. Granitto et al. [79] evaluated the discriminating power of size, shape, color and texture attributes for uniquely identifying 57 weed species using the Naive Bayes classifier. Size and shape attributes showed larger discrimination than color and textural attributes. In total, 12 different color attributes were measured comprising of μ, variance and skewness and three ratios of average histogram values in the RGB channels. Additionally, 21 features corresponding to morphology were extracted. Two different matrices GLCM and GLRL were utilized to portray seed texture features. It was concluded that morphological features has the largest discriminating power, color and texture were less reliable, combined use morphology and color features are slightly better than the combined use of morphology and texture features. Amongst the naive bayes classifier, single ANN and the structuring ten networks in a committee it was demonstrated that the two ANN committee implementations were superior to the naive bayes and single ANN classifier.

J. Paliwal et al. [80] extracted (123 color, 51 shape, and 56 textural) giving total 230 features, for identification of five grain types. Various feature sets, viz. color, shape, texture, and a blend of the three, were assessed for their classification performances using ANN classifier. The accuracy obtained was around 90% . Color, Shape or textural features alone are not sufficient for classification because of similarities of shape and color of chaff and wheat spikelets with the barley and oats kernels. A combination of optimised feature set is very important for classification as an excessive number of elements may thwart the execution of the system.

BPNN and a non-parametric statistical classifier were compared by J. Paliwal et al. [81] for classifying four different grains like wheat, barley, oats and rye.

Various feature models, viz. 123 color, 51 shape, 56 textural and a blend of the three were tested for their classification performances. The BPNN surpassed the non-parametric classifier in nearly all the cases of classification. Best possible set of color, shape, and textural features gave AN accuracy over 96% .

Pablo M. Granitto et al. [82] evaluated the discriminating power of size, shape, color and texture characteristics for uniquely identifying 236 weed species using the Naive Bayes classifier and ANN. Naive Bayes classifier in view of a sufficiently chosen set of classification features showed outstanding performance, as compared to ANN approach.

Ferhat Kurtulmus et al. [83] proposed a classification method to discriminate pepper seed based on neural networks. Image features representing 40 color features (μ, σ, kurtosis, skewness and mean Laplacian from eight color channels - R, G, B, H, S, I, Cb, and Cr), shape features (Area, convex area, minor axis length, major axis length, perimeter, extent, solidity, equivalent diameter, roundness, Hus invariant moments, Zernike moments), and texture features (Haralick texture features, Circular Gabor texture features) were extracted and used to classify pepper seeds. Using sequential feature selection the number of the features was significantly reduced from 257 to 10. An accuracy rate of 84.94% was achieved.

Lilik Sumaryanti et al. [84] developed a system to identify rice varieties using six color features; μ of (R, G, B, H, S, I), four morphological features; area, perimeter, physiological length and physiological width and two texture features.

Classifier used was LVQ neural network algorithm. Identification results using a combination of all features gave average accuracy of 70.3% with the lowest classification accuracy of 37.6% for texture features.

Alireza Pazoki et al. [85] identified barely seed cultivars using ANN using 22 features (6 colors, 12 morphological features and 4 shape factors). Average accuracy found was 80.00% and after selecting features accuracy was increased to 82.22% .

The system for identification of corn varieties using GA and SVM gave the performance accuracy as 94.4% . Min Zhao et al. [86] used color, shape and texture features for the same. Twelve seed color features were obtained comprising μ, σ of RGB, HSI color channels. Geometric features included contour points, perimeter, area, circular degrees, equivalent diameter, major-minor length, stretching the length of the rectangle, maximum inscribed circle, the smallest excircle. Texture features such as μ, variance, smoothness, third moment, consistency, entropy and 7 statistical invariant moments from the gray image were also obtained.

Benjamaporn Lurstwut and Chomtip Pornpanomchai [87] developed a system to recognize a plant seed image. Four shape features (boundary,edge, roundness and ripples, upper and lower seed area ratio), average RGB color feature and the average L*a*b* color feature, five texture features, namely: energy, entropy, contrast, homogeneity, and correlation for GLCM were extracted to recognize a seed. The precision rate as 64.0% was found for testing.

Arman Arefi et al. [88] extracted ninety color, nine morphology and three texture features for recognition of the weed seeds. Finally, only five features μ of R, μ and var. of S, and two shape factors were found to be most significant for weed seeds classification. According to the results, total classification accuracy was 98.40% .

Performance of mere color, shape and texture features along with their combination was tested to classify wheat and barley kernels. F. Guevara-Hernandez and and J. Gomez-Gil [89] classified these kernels using DA and K-NN. It was found that the blend of color, shape and texture features offered higher accuracy than the individual feature. At the end only three features; max. radius, μ of G, μ of y of GLCM for 90o allowed the highest classification accuracy.

e. Classification using Other Features

Performance of mere 93 colour features, 51 morphological, 56 textural, and 135 wavelet features and their combinations was studied for classifying wheat, barley, oats, and rye by Choudhary R. et al. [90]. The classification was done using LDA and quadratic statistical classifiers. And it was found that combination of all features using the LDA classifier gave the best classification accuracies as 99.4% . Wavelet features when used alone showed low performance, but in combination with other features improved its accuracy.

Miroljub Mladenov et al. [91] utilized three diverse methodologies; two sorts of wavelet analysis and PCA. Three classifiers, in light of RBE, were utilized for classification. The results achieved using the created platform were compared with the results acquired by the unscrambler reference platform. The INTECHN platform performed well as compared with the Unscrambler reference platform, under particular test circumstances.

Phan Thi Thu Hong et al. [92] presented a system for classification of rice by analyzing image features of rice seed such as color, shape, texture, and GIST. The classification techniques such as SVM and Random Forest (RF) were used to categorize rice seeds in assorted samples. RF method using simple features provided the best classification with average accuracy of 90.54% .

Hong et al. [93] presented a system for automated classification of rice variety using color, shape, texture, GIST and SIFT features. The three classifiers K-NN, SVM and RF were tested for their classification accuracy. Average accuracy achieved was around 90.54% using Random Forest.

Studying four properties of four Polish red clover varieties was the main purpose of Magdalena Zielinska et al. [94]. The 12 physical, 86 morphological, 45color and 144 textural features were the four engineering properties. The accuracy of classification in view of the physical properties of seeds was observed to be most satisfactory. Bona and Jubilatka varieties were recognized with 100% accuracy taking into account the physical properties of seeds.

Shiqiang Jia et al. [95] investigated the achievability of recognizing coated maize kernels by near infrared spectroscopy (NIRS). For this task SVM, Soft Independent Modeling of Class Analogy (SIMCA), and Biomimetic Pattern Recognition (BPR) were utilized to identify four maize varieties. Three methods were used for placing the seeds for identifying the seeds. Performance of variety models in view of spectra measured by scheme 1 and 2 were observed to be poor. In scheme 3, the SIMCA model achieved an accuracy rate of 97.5% which is better than SVM and BPR models.

Cheng Fang et al. [96] developed a system to inspect the quality of five varieties of rice. An algorithm based on Hough transform was created to investigate the rice seeds with partly closed glumes. The algorithm attained an average accuracy of 96% for ordinary seeds, 92% for seeds with fine crevice and 87% for seeds with partly closed glumes.

2.3.3 Selection of Effective Classifier

A substantial number of studies have been devoted to a BPNN classifier, wherein it was utilized to identify purity of maize seeds based on DWT and BPNN [18], classify wheat family [26,40]. NN based on probabilistic NN have been compared with LDA for categorizing 11 wheat varieties, NNs were comparable to the results of the LDA [42].

ANN was also used to classify the areca nuts [45], identify five corn varieties using BPNN combined with Mahalanobis distance [47], identify variety of cotton seeds as BPNN had higher accuracy than the step discrimination analysis method [53], and identify rice varieties [61].

In detecting and classifying pollens grains on a slice, MDC with Feature Selection, MLP and SVM were compared for pollen grain classification. It was shown that the MDC classifier with the Floating Search Method (FSM) feature selector is somewhat superior to the SVM classifier and the MLP classifier showed lower performance as compared to others [65]. BPNN was found to outperform discriminant analysis in identifying rumex, wild oat, lucerne and vetch seeds [68]. NNs are well suitable for complex, non-linear and multi-class problems. Carefully trained networks demonstrate high generalization ability and guarantee excellent performance in training and testing data sets. Amongst different NN architectures, the multilayer feed-forward network is an extensively standard tool for cereal evaluation [77].

ANN was employed to discriminate weed species [43,79,82], as BPNN performed better than simple Bayesian approach [79,82], and better than traditional statistical models [43]. ANN was additionally utilized to identify the unknown grain types [76,80], classify cereal grains, as the BPNN outperformed the non-parametric classifier [81]. From the StatLog project, a comparative study given in [97] conclusion made was that no single classifier is the best for all data sets, in spite of the fact that the feedforward NNs do have good performance over an extensive variety of issues [97]. From recent neural classification activities, it has been proven that, from various conventional classification methods, neural networks are a promising choice [97]. Jayas et al. [98] demonstrated that a BPNN was most appropriate for classifying agricultural produces. In identifying and classifying agricultural products, ANNs have performed better than the statistical classifiers [98]. Because of their ability to deal with non-linearly separable learn patterns, uncertainty, random situations and noise, NNs is very good pattern classifiers. Multi-Layer Neural Network (MLNN) classifiers offer advantages like massive parallel processing, adaptivity and fault tolerance, as compared to statistical classifiers [98].

No one classification method is at all times better than others in terms of classification accuracy. Nevertheless, there are pros and cons to the use of each. Bayesian classification assumes that the attributes are independent with discrete values. Thus, even though it is simple to apply and understand, results may not be acceptable. The K-NN methods entail that the data should be such that distances can be computed which can then be applied even to nonnumeric data.

Outliers are taken care of by looking only at the K-NNs and it is also biased by the value of K. Decision tree method is simple to understand, but may lead to overfitting. To circumvent this, pruning methods might be required. ID3 is pertinent only to categorical data. Enhancement on it, C4.5 and C5, permit the use of continuous data and superior techniques for splitting. CART construct binary trees and consequently may result in very deep trees [99].

2.4 Analysis of Previous Work

Color is one of the most important features in seeds classification and grading. Different seeds and their varieties are identified by their colors [15]. The classification procedure is data-driven so the results cannot be generalized without difficulty to the study of other types of seed [16]. The blue-mean feature was chosen as the most essential feature and it played a very important role in the classification of bulk rice cultivars. The saturation-mean became the second most important feature [17]. Even though the study was done on nonoccluding seed, the automatic severance of occluding seed need to be solved [23]. An ANN could be utilized for varietal recognition of barley kernels [25]. The performance of General Regression Net was least suited for classification process due to the fact that they perform well on sparse data as compared to the larger data sets [28]. After determining the potential of three illuminations; FTL, IL and FRL; FTL was found to have more potential as it gave higher accuracy using textural features [41]. Morphological features have low discrimination capabilities, and that a set of simple features measured over color distributions provides good separation among soyabean grades [55]. P.M. Granitto et al. [66] provided evidence that boosting naive bayes and neural classifiers does not compensate the discriminating power of color features. So, the color features as classification attribute could not be avoided by simplifying operating conditions. The majority of the color features were from the R band of the sample images. The first 3 histograms from the R band were the most significant color feature and short run from all the color bands was found to be the significant from the textural features [76]. Morphological and textural characteristics could possibly be used which reduce the hardware cost as these features could be extracted from black and white images, and the restriction of illumination conditions could be removed, support for this claim comes from [79].

After the comparison between the color features and the texture features the following observations were made. The rankings of color features based on HSI and RGB features, indicated that HSI based features were least important as compared to the RGB based features. In case of texture features, GLRL performed better in the classification as compared to the GLCM. The features obtained using the G channel contributed more towards classification than the R and B channel [81]. A combination of optimized feature set is very important for classification as too many features might hinder the performance of the system [81]. All the feature models failed to classify the grains with high accuracy. An optimized feature set is needed because the existence of excessive features hinders its performance [80, 81, 82]. A BPN is suggested for classification of cereal grains [81]. For very basic applications the framework can be implemented using black and white seed images. An improved control of illumination conditions is required to improve the discriminating power of color and texture features [82]. Shape and size features were discovered to have a larger discriminating capacity than color and textural ones for weed identification [82]. Mean and variance of saturation increased the accuracy while kurtosis did not improve the accuracy, so kurtosis was not used [88]. The GIST feature appeared to be exceptionally proficient for scene classification, yet it is not competent in seed variety classification as it didn't demonstrate its advantage in delineating the seed shape which was a crucial factor for classification [92]. Like the GIST feature, SIFT does not give advantages in delineating the seed shape, particularly when the shapes of seeds are similar. So, the basic features proved to be a good choice for the assessment of rice seed purity [93]. Table 2.1 gives Analysis of seed feature extraction and classification techniques.

2. Conclusion

The challenges and opportunities that were encountered during the review were as follows. Figure 2.2 presents statistical data showing the proportion of feature extraction methods used in the review. Most of the feature extraction algorithms use the color, shape and texture features for classification. Utilizing these features can misclassify the seeds because of the inter-class and intra-class variations. So, a need for new features was found which would really discriminate the seed.

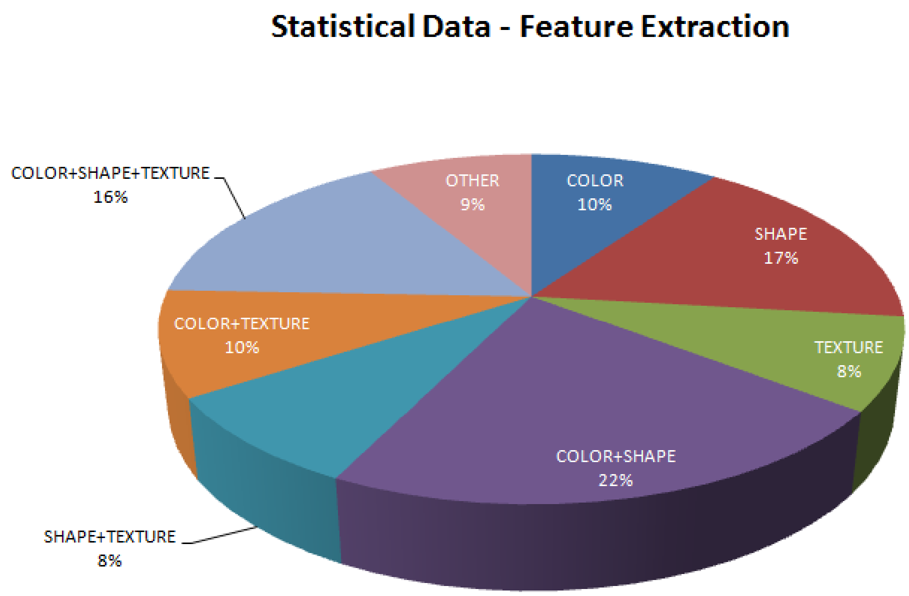

Figure 2.2: Statistical data showing proportion of feature extraction papers

Secondly, Figure 2.3 presents statistical data showing the proportion of classifiers used in the review. NNs have been used most of the time as they are universal functional approximators, are data driven self-adaptive, are nonlinear models, due to which are supple enough to model actual real world problems. Finally, NNs can estimate the posterior probabilities, due to which classification rule can be established for performing statistical analysis [97].

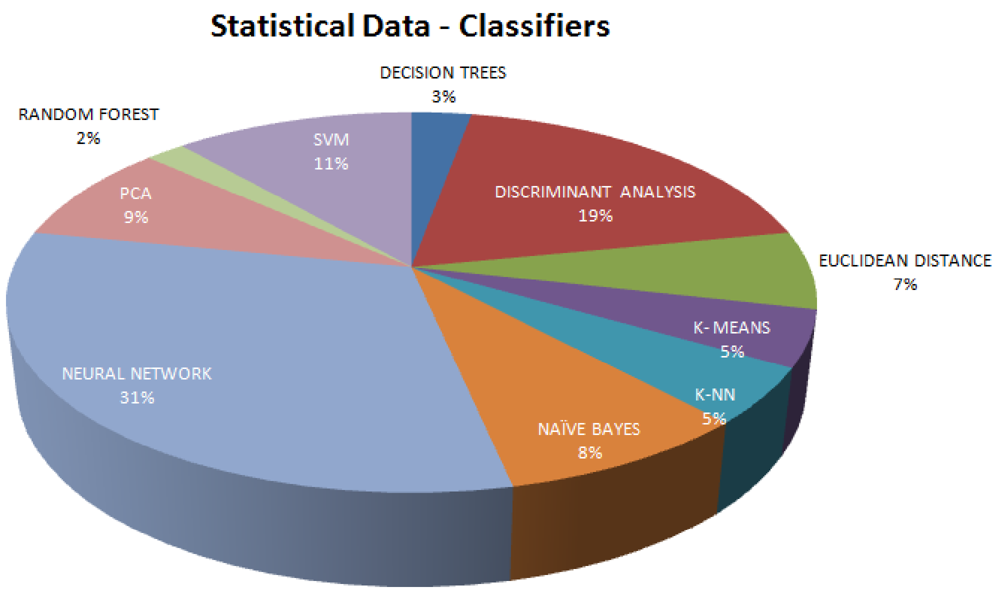

Figure 2.3: Statistical data showing proportion of papers using classifiers

Third, the vast majority of the existing algorithms extract a huge number of features for classification. Extraction of this huge number of attributes increases the computation time. For any system, to be utilized on a large scale, operational speed is a crucial factor. So, a need to select the features having more discriminating power was found.

Figure 2.4 shows seed technological development at a glance which indicates the work done yearwise (2001-2010, 2011-2014 and 2015-2016). The need of novel features, optimal feature set and features capable of reliably discriminating the seed was found out.

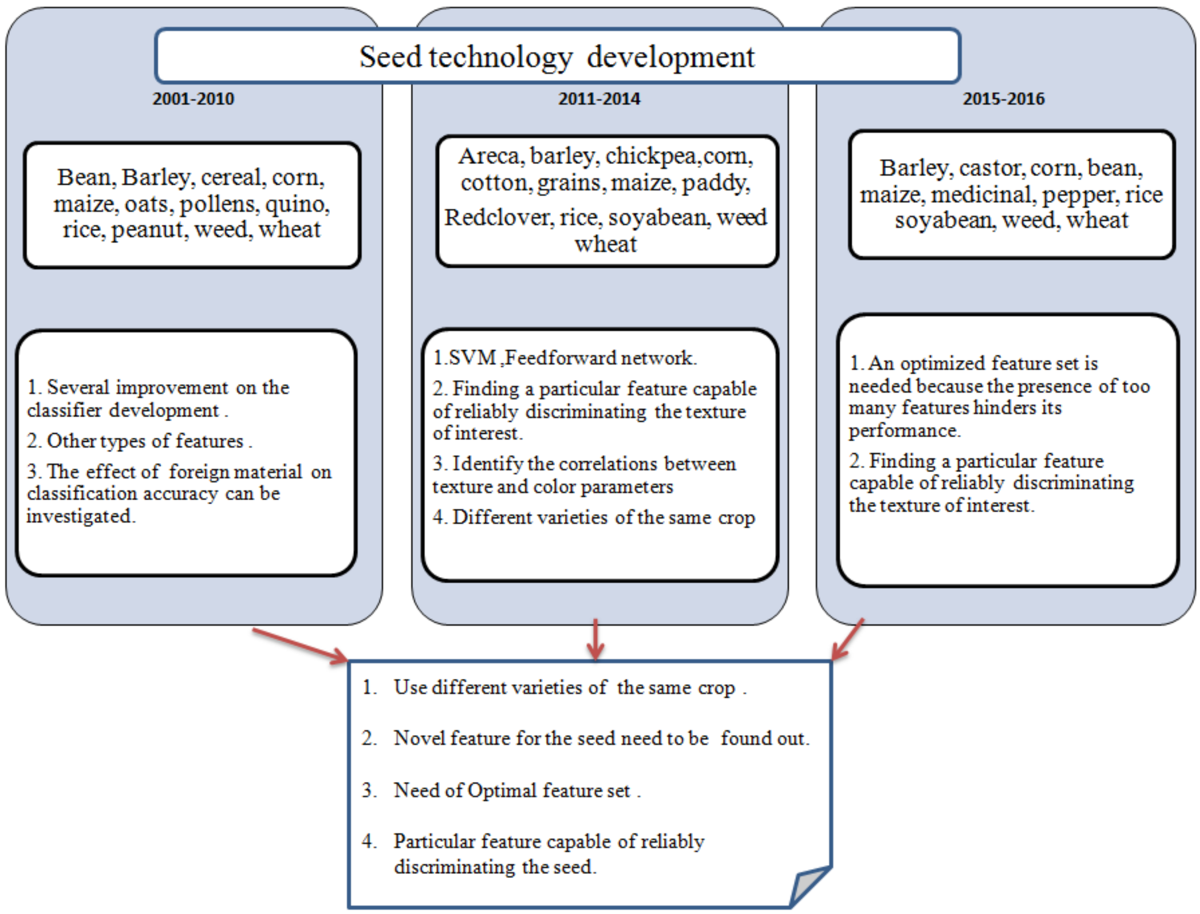

Figure 2.4: Seed technological development at a glance

This section has presented the survey on diverse research activities related to existing seed classification work related to this research. The graphical summary has been presented showing relation of number of papers per feature extraction technique and classifiers. Finally, the section dealt with challenges and opportunities those are addressed in this research work.

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