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Real-Time Quality Assurance of Fruits and Vegetables using Hybrid Distance based MKELM Approach

1. Dr G. Devika, Head and Assistant Professor, Department of Computer Science, Mannar Thirumalai Naicker College, Madurai, Tamilnadu, India.
gdevika2016@gmail.com

2. Priya, Assistant Professor, School of Agriculture, Graphic Era Hill University, Dehradun, India.
priyachugh056@gmail.com

3. Dr Chandra Sekhar Rao Bandaru, Associate Professor, Department of Science & Humanities, Vardhaman College of Engineering, Autonomous, Shamshabad, Hyderabad, Telangana, India.
drbrchandrasekhar@gmail.com

4. Dr Romala Vijaya Srinivas, Assistant Professor, BBA Department, Kl University, Vaddeswaram, Andhra Pradesh, India.
romala.vijay@gmail.com

5. Prof. (Dr.) Nitin Girdharwal, Professor, Prestige Institute of Management & Research, Indore, India.
n.girdharwal@gmail.com

6. Dr M. Nirmala Devi, Assistant Professor in English, St.Martin's Engineering College, Secunderabad, Telangana, India.
nirmalmphil@gmail.com

***Abstract* – Sustainable development relies on a number of pillars, one of which being agriculture. Sustainable agriculture, in light of expected population expansion, must ensure food security while remaining economically and socially viable and having a minimal impact on biodiversity and natural ecosystems. Deep learning has shown to be an advanced method for analyzing large amounts of data, having applications in fields as diverse as image processing and object recognition. Recently, it's being used in the fields of food engineering and science. Food recognition, quality detection of produce, meat, and seafood, the food supply chain, and contamination were only some of the problems these systems set out to solve. Artificial intelligence (AI) is a common tool in the field of precision agriculture for making predictions about the quality of harvested crops. This is especially true when assessing crops at various post-harvest stages. Certain postharvest diseases or damages, like rot, can completely wipe out crops and even produce toxins that are hazardous to humans, making disease and damage identification a top priority. Preprocessing with a gabor filter, enhancement with HE, segmentation with a K-means algorithm, and feature extraction with LBP and BIC make up the suggested method. Lastly, DB-KELM is used to train the model. As compared to ELM and KELM, the proposed method performs better.**

***Keywords*— Gabor Filter (GF), Distance Based (DB), Multiple Kernel Extreme Learning Machine (MKELM).**

I. INTRODUCTION

Over the past few years, there has been a dramatic shift in how much emphasis is placed on product quality. There has been a movement in customer tastes toward things of the highest possible quality due to rising consumer knowledge of environmental, nutritional, and health issues, growing competition, and surplus production of various horticultural commodities. A unique and comprehensive technique of assessing product quality, especially for those destined for the fresh market, is therefore becoming increasingly important. New marketing strategies are being developed to suit the demands of consumers and maintain competitiveness in the European and global trade marketplaces (such as quality management systems and labeling). Throughout the past decade to fifteen years, there have been major changes in the national and worldwide markets for fresh food, notably fruits. These changes are pervasive throughout the marketing process, from creation to collecting to distribution to packaging to consumption to quality control. Everything from the infrastructure to the individual components has been improved and updated with the end user and financial bottom line in mind. The fresh fruit and vegetable sector has grown to be worth billions of dollars. You don't even have to set foot in a fruit stand to make a profit on fruit purchases. Improvements in shipping and communication have allowed wholesalers to do business with suppliers all throughout the United States and even the world. The fresh produce market has seen a rise in investment from retailers, wholesalers, and intermediary distributors. There are connections between the major national wholesale marketplaces and the secondary, regional markets. The food industry's approach to ensuring product quality is evolving rapidly. The Quality Control perspective is giving way to the Quality Assurance and eventually, Quality Management perspective as far as quality evaluation methods are concerned. As a result of these breakthroughs, attention has radically shifted from quality inspection to the enhancement of quality-enhancing procedures. They also assume that the priority should be shifted from the product to the consumer in terms of quality. Instead of providing intellectual leadership in reshaping thought on quality as it applies to processed products, academic research in food science has generally viewed quality as a tool to evaluate other objectives (such as food product development, food process development, new package assessment). So, the definition of food quality continues to focus on objective characteristics rather than individual tastes. Researchers inspect each fruit carefully, classifying them according to their quality[1]Premium fruit is more expensive because of the higher quality it provides. Knowing the quality of the product being delivered to customers is so crucial in the agriculture and food delivery service businesses. Visual inspections of fruit are common, but it is challenging to automate this process. Yet, similar to how a human brain learns, a machine need a series of images and some pre-processed inputs in order to develop a system that can execute the task that an investigator would while checking the quality of fruits. Vegetables and fruits must be examined for their characteristics in order to be graded. The same process will be mechanized for better accuracy and fewer mistakes. Manually sorting and evaluating samples is time-consuming and error-prone. An automated system based on these quality parameters will complete the job more quickly and accurately. This method of color recognition is a significant step forward in computer science. Fruits and vegetables can be organized into tiers according to size and hue using color-based classification. An artificial neural network is used to determine the type of fruit based on its size, shape, and color. The proposed approach uses Preprocessing, Enhancement of Image, segmentation, Feature extraction and training the model.

II. LITERATURE SURVEY

Several different sensors can be used to determine the quality of produce[2] Sensors can check if the fruit is edible and hence provide a rough assessment of its freshness. It may be able to evaluate the watermelon's internal quality using acoustic impulse response[3]. Tissue quality assessment using laser-induced fluorescence. The freshness of the produce is determined using ultrasonic technology. Dragon fruit ripeness may be determined with the use of image processing and a deep learning technique [4]. Image processing-based mango recognition and sorting method [5]. The application of image processing methods for classifying produce and detecting defects [6]. Several image processing technologies can replace human judgment and increase accuracy when used to categorize fruit based on their flavor, nutritional content, aroma, etc[7]. The use of fruit and vegetable picture data for quality prediction has been the subject of numerous methodologies. Learning more about the topic by checking out the works listed here. The most crucial discoveries from the previous research were the model architectures and hyper parameters. In [8]use an ANN variant for fruit recognition. The photographs of the fruits were taken with a digital camera; the backgrounds were then removed using a split-and-merge technique; and last, the images were shrunk to 256x256 resolution. Our authors [9]introduce a framework for fruit classification using deep learning. The framework is based on two separate deep learning architectures. One is a refined deep learning model for 16-by-16 visual geometry, and the other is a 6-layer convolutional neural network model for lighting. Both publicly available and private color image datasets are used to evaluate the proposed system. The texture, color, and edge qualities of fruits and vegetables are just a few of the many factors that go into their classification. Scientists have scanned the fruit with a gas sensor and high-performance liquid chromatography instruments in the near-infrared[10]. By factoring in prior knowledge during distribution computation, [11]were able to minimize the number of training samples to around ten photographs while retaining a satisfactory recognition rate. Even with this development, the difficulty mentioned in this proposed approached that requires speed for on-line operation remains unrealistic due to exponential rise with the number of parts. Even with sophisticated technology, the accuracy of these methods is less than 84.78% [12]rendering them largely ineffective. Researchers have taken an interest in image-based fruit categorization as a feasible approach due to its low cost and high performance. Using features generated from the fractional Fourier entropy[13] implemented a BPNN (FRFE). Authors proposed a hybrid genetic algorithm improvement to replace BPNN (IHGA). Improve your results with[14].'s novel biogeography-based optimization and feedforward neural network (BBO-FNN). The interior quality of the fruit has a significant impact on shipping, harvesting, storage, and other aspects of handling, making evaluation a vital step before distribution. So, they should do everything is necessary to meet these standards [15]. A lot of people are trying to figure out how to measure the quality of fresh food consistently and come up with a standardized set of measures to use. Prof. Margarita Ruiz-Physical Altisent's Properties Laboratory (LPF), for example, has been undertaking theoretical and applied research on fruit quality evaluation with regard to quality criteria and instrumental measurement of quality in fruits [16]Researchers and regulators in the commercial nutrition industry are paying increasing attention to internal quality variables such total acidity, soluble solids concentration, and hardness [17]. Some of the ways that fruit quality has been measured in the past include sugar concentration, soluble solids content, acidity, firmness, and total acids. During the past 40 years, several research and fi eld observations have demonstrated that between 40 and 50 percent of horticulture products grown in developing nations are wasted due to severe bruising, water loss, and deterioration in the postharvest period. The nutritional value of fresh vegetables is also significantly diminished when it sits around for too long. The freshness and quality of vegetables depend on many factors. A multitude of factors, the aggregate of which is higher than the parts individually, determine the rates of deterioration and spoilage [18]. If these problems aren't handled properly, it can lead to significant post-harvest losses. According to Kader, over a third of all perishable food that is never sold goes to waste (2002). Another estimate puts the percentage of produce lost between harvest and table at 30-40%.[19]. Agriculture and the agri-food industry now place a premium on ensuring and improving food quality and safety in a competitive environment. As a result, many different areas and countries have launched efforts and quality assurance systems in the agrifood sector[20][21]. The majority of action programs are grounded in the business management concept of "quality management" (QM), which aims to improve food quality through more careful oversight of the production and distribution processes, the implementation of additional measures to ensure the food's safety, and the expansion of

QM to cover the industry's unique needs in this regard. Compost nitrogen immobilization, nuisance potential, leaching, and phytotoxicity [22][23] are all affected by pathogens, inorganic and organic potentially toxic compounds, and stability, but these standards are most important from the perspective of soil and public health protection. Composting regulations have become increasingly diverse across the globe in an effort to maximize both environmental and public health protection and organic matter recycling. In addition, the risk assessment technique used in the USA may differ significantly from the EU's cautious approach with regards to the recognized limit values for a number of critical elements, such as heavy metals. There is a large disparity between the northern and southern parts of the EU in terms of the limit values adopted by the member countries, reflecting not only the different levels of progress on source separation of the biodegradable fraction of MSW but also the different needs in soil organic matter. Compost quality is a subjective term that is difficult to define because its meaning differs from industry to industry, person to person, and country to country.

III. PROPOSED SYSTEM

The topic of classifying fruits and vegetables is addressed by a number of proposed architectures and algorithms. It begins with the presentation of a dataset, followed by the application of several machine learning and deep learning algorithms. classification systems for fresh produce. The proposed model's data flow is depicted in Fig. 1.

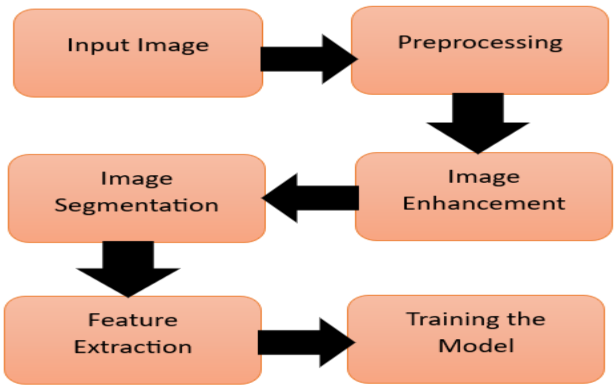

Fig. 1. Flow Diagram of Proposed Model

A. Data Preprocessing

Image filtering and enhancement is crucial for optimal outcomes. As a result, the outcomes of segmentation for photos captured on mobile devices may vary. An image is preprocessed when it is resized, noise is removed, and the quality of the image is improved. Artifacts, such as noise, can appear in digital photographs. When capture quality is low, even a trivial thresholding job might become challenging. So, it is critical to eliminate all forms of noise from the picture. Image noise refers to the unpredictability of a picture's lighting or color statistics. Many types of noise such as Gaussian, salt and pepper, shot, quantization, grain, and periodic can be observed in photographs. These distracting noises can be eliminated with the help of filters like median filters and Wiener filters. It's possible to utilize a variety of morphological operations to cut down on background noise. Images can be smoothed using Gaussian filtering, while the brightness of individual pixels can be adjusted using median filtering [24]. In this scenario, noise was removed using a Gaussian filter (GF). Gaussian filtering preserves the image's essential qualities while giving less weight to individual pixel intensities in favor of an average based on those of neighboring pixels. This technique allows you to smooth the image without destroying its original aspect ratio or border quality. Gaussian kernels calculated from the cumulative standard deviation are used to smooth it out. Let's have the Gaussian function F(z) and its standard deviation SD(p):

$$F(z) = \frac{1}{\sqrt{2\pi\omega^2}} f^{\frac{z^2}{2\omega^2}} \tag{1}$$

$$\omega = \sqrt{\frac{\sum_k (Z_k - \bar{Z})^2}{m-1}} \tag{2}$$

whereZ_k is an individual value, $Z'$is the average, and m is the total number of observations.

B. Enhancement of Image:

After being filtered, photos are improved so that more information is visible to the naked eye. +e histogram equalization improves contrast by sharing each pixel's intensity value, resulting in an output image with a constant histogram and uniform intensity distribution. This method boosts the overall contrast of the image on a regular basis when the image's practical data is determined by strict contrast values. The intensity values in the histogram will be more uniformly distributed after applying this strategy. Hence, increasing contrast may be useful in places where there is already little to no local contrast. Histogram equalization effectively disperses the most commonly occurring intensity values.

C. Segmentation of Image

The image is then segmented using a K-Means clustering approach. Pictures are divided into four groups, with the bulk of the afflicted area falling into one group. Using a given set of characteristics, k-means clustering algorithms divide the objects at hand (pixels in our scenario) into K distinct groups. Minimizing the squared distance between each data object and its cluster is used to perform the categorization [25]. In this proposed approached, K means clustering was performed using the squared Euclidean distance.

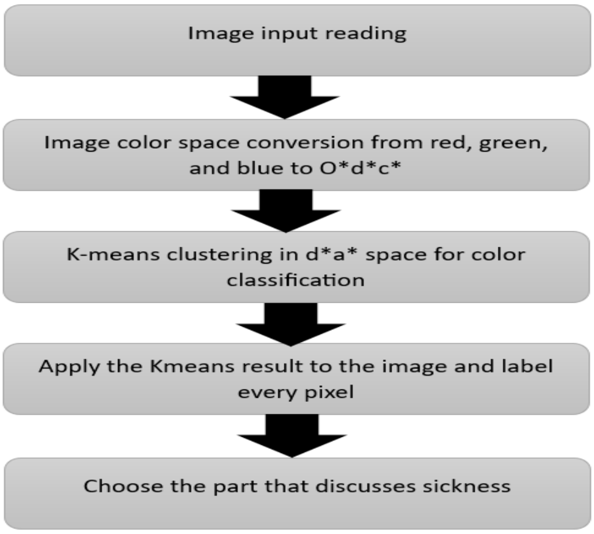

Fig. 2. Flow Chart of K-Means Segmentation

As $o^*d^*b^*$ color space stores color information in only two channels (i.e., $d^* and\ b^*$ components), they have used it to segment images with less processing time.

D. Feature Extraction

The system's precision and efficacy are verified through the extraction of some cutting-edge color and texture attributes. Global color histogram (GCH), local binary pattern (LBP), and border/interior classification are the features utilized in the categorization of fruits and vegetables and the diseases that affect them (BIC)

1) GCH

The GCH is the most elementary method of encoding visual data. The likelihood of a pixel being a specific color is represented as a series of ordered numbers in a Matrix [26]. Scaling bias can be eliminated and the number of unique colors can be decreased by using uniform normalization and quantization.

2) LBP

LBP is calculated for a given input image pixel by making a neighbor comparison as follows.

$$LBP_{M,Q} = \sum_{m=0}^{m-1} U(w_m - w_d)2^m \quad (3)$$

$$s(z) = \begin{cases} 1, z \geq 0 \\ 0, z < 0 \end{cases} \quad (4)$$

where w_d is the central pixel's value, w_m is the neighboring pixels' values, Q is the neighborhood's radius, and M is the number of neighboring pixels. The coordinates of w_m are $\left[Qcos\left(\frac{2\pi m}{M}\right), Qsin\left(\frac{2\pi m}{M}\right)\right]$, if w_d is at (0, 0). If a neighbor's value is not displayed in the picture grids, it is possible to interpolate a reasonable approximation. Let the image size be $K * I$.A histogr am is then constructed to stand in for the texture image once the LBP code of each pixel has been calculated.

$$E(l) = \sum_{k=1}^{K}\sum_{i=1}^{J} \begin{matrix} h\big(LBP_{M,Q}(k,i), l\big), l \in [0, l] \\ f(z,x) = \begin{cases} 1, z = x \\ 0, otherwise \end{cases} \end{matrix} \quad (5)$$

L being the highest possible value for the LBP code. To calculate the LBP feature, we use the values "M" and "Q"of "8" and "1", respectively, in this experiment.

3) BIC

The approach determines BIC by assigning border and interior statuses to picture pixels. If the quantized colors of the four pixels to its top, bottom, left, and right are all the same, then that pixel is considered to be inside the image. Otherwise, it's considered to be on the frontier. Two color histograms are then calculated, one for border pixels and another for inner pixels, based on the classifications of the picture pixels.

E. DB-Multiple KELM MODEL:

1) ELM

When it comes to training single-hidden-layer feedforward networks, Extreme Learning Machine is unrivaled (SLFNs). ELM has had extensive application. Both the lightning-fast learning curve and the impressive generalization results are among the key benefits. These benefits stem from ELM's least squares approach to learning the remaining weights and its random generation of the weights between the input layer and the hidden layer. For illustration's sake, here is the output function of an SLFNs with o hidden layer nodes and 1 output layer node:

$$h(z) = e(z)\alpha \quad (6)$$

where α is the weights between the output land hidden layers and $e(z)$ is the value vector of the hidden layer that transfers the original features into the new feature space $e(z) = [F(b_1, c_1, z), \dots, F(a_o, b_0, z)]$. For training SLFNs, ELM is unique since it can employ any $e(z)$ where $G(b_k, c, z)$ is a nonlinear piecewise continuous function. Examples of such functions are the sigmoid function and the Gaussian function. In addition, ELM allows for the use of any continuous probability distribution in the selection of b, the weights between the input layer and the hidden layer, and c , the bias of the hidden nodes. Therefore, is the sole parameter that ELM needs to acquire knowledge of. α The following optimization problem [7] is used by ELM to learn:

$$\min_{a} \frac{1}{2}\|\alpha\|^2 + \frac{1}{2} d \sum_{k=1}^{M} \varphi_k^2 \quad (7)$$

$$s.te(z_k)\alpha = x_k - \varphi_k \quad (8)$$

where $\{z_k, x_k\}$ are examples used for training. KKT theorem states that the value of can be determined using

$$\beta = E^S\left(\frac{1}{D} + EE^S\right) \quad (9)$$

where $y = [x_1, \dots, x_m]$ and $E = [e(z_1, \dots, e(z_m)]$. when M is little compared to $M \ll O$, one can use (9).

2) DB-KELM

Given that the point of MKELM is to build a new kernel that is better suited for problem processing, it is important to think about what constitutes a "good" kernel. In a broad sense, kernel can be understood as a degree of closeness metric [27]. The entries in a kernel matrix each stand for the degree to which two samples are alike. From this vantage point, a "good" kernel can accurately depict the degree to which two samples are alike. That is to say, if the similarity between two sample pairs is high, then the value they share in the "good" kernel will also be high. It's advocate using distance-based multiple kernel ELM to achieve this end. It builds a "good" kernel based on the "label distance" between sample pairs, which will be specified in the next section. DB - MKELM. The first step is for it to pick up a brand-new kernel. In the second phase of KELM, the updated kernel is implemented.

3) Multiple KELM

The second step of DB-MKELM involves the utilization of the newly learnt kernel in the training and testing scenario of the kernel-based ELM. As a result, it can express the DB-MKELM output function as:

$$\begin{bmatrix} L_{new}(z, z_1) \\ \vdots \\ L_{new}(z, z_m) \end{bmatrix}^S \left(\frac{1}{D} + L_{new}\right)^{-1} X \tag{10}$$

for some set $Y = [x_1, X_M]^T$. DBMKL-ELM now efficiently handles classification and regression problems using a multi-kernel approach. In order to solve a classification or regression issue, DB-MKELM first learns the coefficients of a set of base kernel combinations. The system then determines an updated optimum kernel. In the end, the remedy for the issue can be found by (10).

IV. RESULT AND DISCUSSION

Various criteria have been used to compare algorithms and find the most effective one for the task of detecting quality assurance of fruits and vegetables. The success of machine learning algorithms is measured in three ways: accuracy, recall, and precision. It is possible to calculate all of these quantities with the use of a Confusion matrix. Each model's performance was evaluated in accordance with these criteria. Both the original data and the oversampled data were used to evaluate the models, highlighting the importance of sampling.

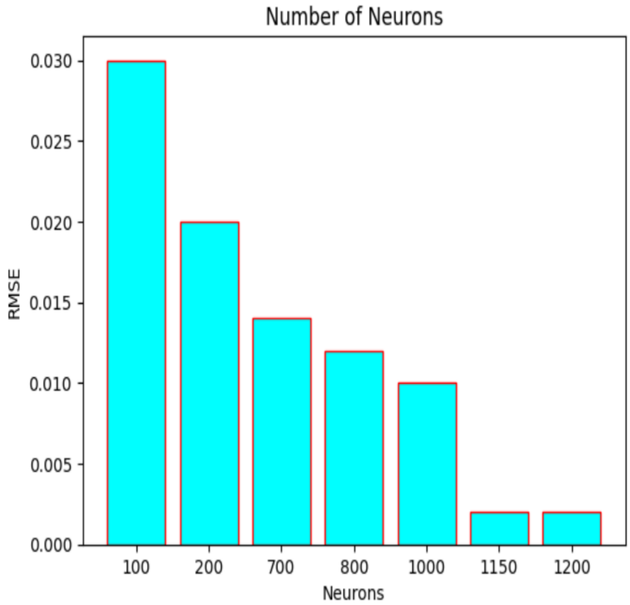

Fig. 3. RMSE Comparision

Different numbers of neurons are set for recognition, and the recognition results are displayed in Figure 3; this is done so that the ideal structure can be chosen based on the determined activation function. It is clear that the network's recognition effect improves dramatically as the number of neurons in the hidden layer grows.

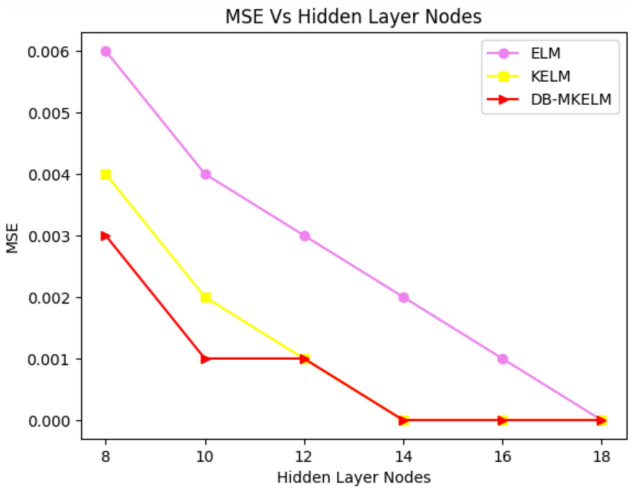

Fig. 4. MSE Vs Hidden Layer Nodes Comparision

Figures 4 and 5 depict the correlation between the hidden layer node modifications and the mean square error of the training and prediction samples, respectively.

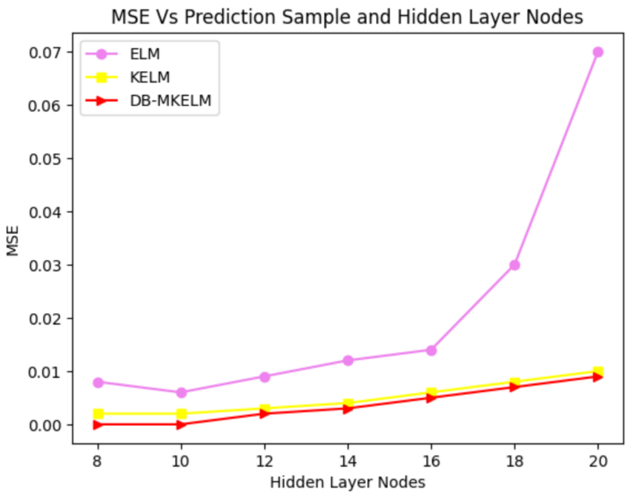

Fig. 5. MSE Vs Prediction sample of Hidden Layer Nodes Comparision

It is clear that the training and prediction of samples are profoundly influenced by the number of hidden layer nodes, and that the training error reduces with the rise of the number of hidden layer nodes until the error is zero. Prediction accuracy increases as the number of hidden layer nodes decreases. Overfitting causes an ever-increasing inaccuracy as the number of nodes in the hidden layer grows. This has a direct impact on the prediction error.

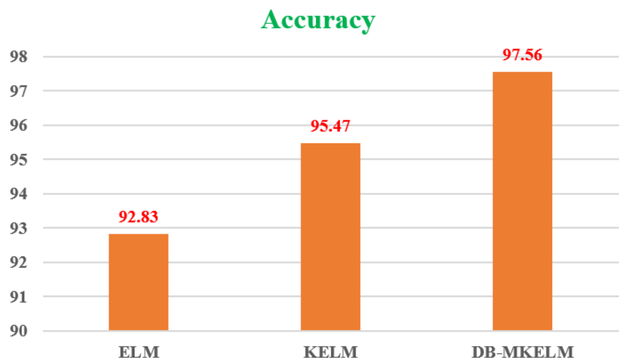

Fig. 6. Accuracy Comparision of the Models

Fig. 6 shows a comparison of the models' accuracy. When compared to the ELM and KELM models, the proposed method fares very well.

V. CONCLUSION:

The way a fruit looks is a major indicator of its overall quality. Its external attractiveness affects not just their market value, but also the consumers' tastes and decisions. The appearance of food is typically evaluated by looking at its color, texture, size, form, and any obvious faults. It takes a lot of time and effort to manually control the outward quality of fruit. The proposed method for picture preprocessing makes advantage of Gaussian elimination. In this process, noise is removed from images using Gaussian elimination. Image quality is enhanced as a result of this preprocessing. Higher quality images facilitate more accurate labeling. then histogram equalization is used to improve the image. The histogram equalization technique is used to improve the quality of an existing image set. The precision of the classifiers benefits from this as well. K-means clustering for data segmentation. LBP and BIC feature extraction. Finally, MB-MKELM Model education. The experimental outcomes demonstrate the efficacy of the strategy in locating a high-quality kernel capable of producing best-in-class classification results. The DB-Multiple KELM model can be adjusted for both classification and regression. The proposed model outperforms other two models such as ELM and KELM and produces an accuracy of about 97.6%.

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