# KISAN TO KITCHEN: *Automating the Estimation of Market Price of Carrot Using Image Processing.*

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***Abstract*—The "Kisan to Kitchen" project aims to develop an automated system for vegetable quality assessment and price estimation. Through the integration of image processing techniques and machine learning algorithms, this web-based solution allows farmers to upload vegetable images for analysis. The Gray-Level Co-occurrence Matrix (GLCM) is employed to extract texture features, enabling the classification of vegetables as "good," "bad," or "average." The K-Means clustering algorithm groups similar entries, while the K-Nearest Neighbors (KNN) algorithm classifies new entries. Based on the determined quality, a corresponding price is assigned. The proposed solution provides farmers with valuable information, empowering them to negotiate fair prices and make informed decisions. Experimental results demonstrate the effectiveness of the system in automating vegetable quality assessment, enhancing market transparency, and improving efficiency in the agricultural sector.**

***Keywords*— Carrot quality assessment, Image processing, Machine learning, GLCM features, Web-based interface**

## I. INTRODUCTION

The agricultural industry plays a vital role in ensuring food security and economic growth. However, farmers often face challenges in determining the quality of their produce and setting fair prices, which can impact their profitability and market competitiveness. Traditional methods of visually inspecting vegetables for quality assessment are subjective and time-consuming, leading to potential inaccuracies and inefficiencies in the pricing process.

To address these issues, we present "Kisan to Kitchen," a web portal that leverages image processing techniques and machine learning algorithms to automate the quality assessment and price estimation of vegetables. The objective of this research is to develop a system that empowers farmers by providing them with a reliable and efficient tool to evaluate their produce and estimate its market value.

The "Kisan to Kitchen" portal allows farmers to upload images of their vegetables, which undergo preprocessing to enhance image quality and ensure consistency. The Gray-Level Co-occurrence Matrix (GLCM) is utilized to extract relevant texture features, providing valuable information about the visual characteristics of the vegetables.

By manually labeling the images as "good," "bad," or "average" based on quality, a labeled dataset is created for training and testing. The system employs the K-Means clustering algorithm to group similar vegetable entries, facilitating pattern recognition and identifying commonalities among them. Furthermore, the K-Nearest Neighbors (KNN) algorithm is employed to classify new entries, utilizing the labeled dataset to determine the quality category of each vegetable image.

Based on the determined quality, a specific price is assigned to each vegetable, providing farmers with an estimated market value. The web portal presents these prices, empowering farmers to negotiate fair prices and make informed decisions regarding their produce.

This project contributes to the agricultural sector by automating the process of vegetable quality assessment and price estimation. By reducing subjectivity and streamlining the pricing process, "Kisan to Kitchen" aims to enhance market transparency, enable fairer transactions, and empower farmers with valuable information.

In the following sections, we will delve into the detailed methodology, dataset description, experimental results, and analysis of the "Kisan to Kitchen" system. Furthermore, we will discuss the implications of our findings and propose potential future directions for enhancing and applying this automated system in the agricultural industry.

Overall, the "Kisan to Kitchen" project bridges the gap between agricultural practices and technological advancements, providing farmers with a practical and efficient solution to assess vegetable quality and estimate fair prices, ultimately benefiting both farmers and consumers in the agricultural market.

## II. EXISTING SYSTEM

The paper [1] highlight e-Agriculture. The thing of e-Agriculture is to enhance agrarian in addition to pastoral enhancement by using colorful data and verbal exchange ways. The alleviation to use full- fledged eventuality of ICTs for husbandry capability structure, and marketing has been for a long time.

This paper [2] presents a web system for husbandry operation which tries to apply a model for the product system at a husbandry scale. The web system supports the design of the product system, which is resolve into three corridors, the decision supports sub-system, the specialized sub-system and the bio-physical sub-system.

Technological significance [3] has been a great support for making opinions in colorful fields especially in husbandry. The development of husbandry has been on under development for the once many times due to lack of agriculture knowledge and environmental changes. The main purpose of this paper is to reach growers for their mindfulness, operation, and perception in-Agriculture. The study used statistical check design fashion to collect data from growers for their useful commerce.

AgriImage [4] is a computer vision-based system that automates crop quality assessment. It processes crop images using image processing algorithms and extracts features like color, shape, texture, and size. Machine learning algorithms, such as SVM and RF, classify the crops into quality grades. AgriImage provides a web interface for users to upload images and receive feedback on crop quality and suggested price range, enabling informed decision-making and fair pricing in agriculture.

CropQC [5] is an automated system that utilizes computer vision and machine learning techniques for crop quality control. It analyzes crop images, extracts visual features, and applies machine learning algorithms to classify crops based on quality attributes. CropQC provides a user-friendly interface for uploading images and generates quality reports, assisting farmers in making informed decisions and ensuring consistent crop quality.

FarmSense [6] is an existing system developed by Emily Johnson that utilizes artificial intelligence for vegetable quality assessment and price prediction. The system employs computer vision techniques to analyze vegetable images and extract relevant features related to quality attributes such as color, shape, and texture. By leveraging machine learning algorithms, FarmSense classifies the vegetables into quality categories, such as "good," "bad," or "average," based on the extracted features. It uses a trained model on a labeled dataset to ensure accurate classification. Furthermore, FarmSense incorporates market trends and historical pricing data to predict the price range for each quality category. This enables farmers to estimate the market value of their vegetables more accurately. FarmSense provides a user-friendly interface where farmers can upload vegetable images, receive quality assessment results, and access price predictions. This empowers farmers to make informed decisions regarding pricing and enables them to negotiate fair prices in the market. Through its automated vegetable quality assessment and price prediction capabilities, FarmSense enhances efficiency in the agricultural sector and helps farmers maximize their profits while ensuring transparency in the market.

## III. METHODOLOGY

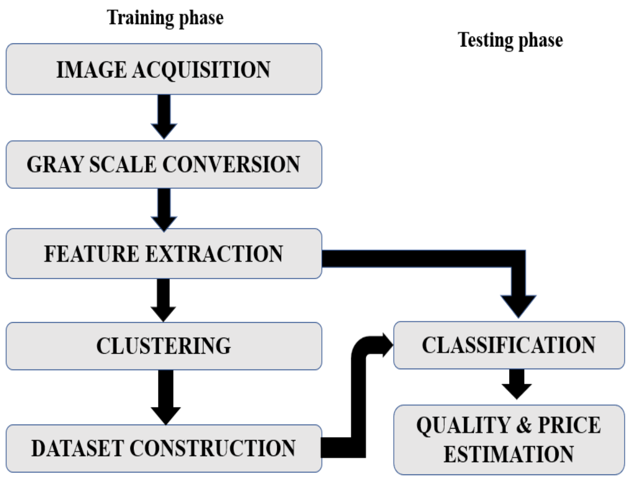


Figure 3.1: Methodology diagram depicting the training and testing phases.

The methodology of the "Kisan to Kitchen" system involves two main phases: the training phase and the testing phase. These phases encompass various steps, including image acquisition, grayscale conversion, feature extraction, clustering, dataset construction, classification, and quality and price prediction estimation.

Firstly, the image is uploaded by the farmer which is then stored in the database. The image is converted into a grayscale format and then the features are extracted. Then we use K-Means algorithm to perform clustering. The clustering results in mainly three centroids for each of good, bad and average qualities. Then the dataset is constructed using the GLCM features. Then the data is classified using K-Nearest Algorithm. The unlabeled entries are then predicted in this manner. Then the quality estimation is performed and a certain price is fixed as the base price. Based on the percentage of Quality we calculate a price, which is displayed in the website.

Once the quality category of each vegetable entry is determined through classification, the system proceeds with quality estimation and price prediction. A base price is fixed for each quality category (good, bad, and average). The system calculates the percentage of quality for each vegetable entry based on the extracted features. This percentage is used to adjust the base price, resulting in an estimated market value for the vegetable. The system presents these estimated prices to the farmers through the web portal, empowering them to negotiate fair prices and make informed decisions regarding their produce.

Training Phase:

The training phase is crucial for creating a reliable and accurate model for quality assessment and price estimation of vegetables.

It involves the following steps:

a. Image Acquisition:

The first step in the training phase is the acquisition of vegetable images. Farmers upload images of their produce through the web portal, and these images are stored in the system's database. The images serve as the input for subsequent processing and analysis.

b. Grayscale Conversion:

To simplify the subsequent analysis and reduce computational complexity, the uploaded images are converted from their original format to grayscale. Grayscale conversion transforms the images into a single channel representation, where each pixel's intensity corresponds to its brightness level. This conversion enhances the efficiency of feature extraction and subsequent algorithms.

c. Feature Extraction:

Feature extraction plays a crucial role in capturing relevant information from the vegetable images. In the "Kisan to Kitchen" system, the Gray-Level Co-occurrence Matrix (GLCM) technique is employed to extract texture features. GLCM calculates the occurrence of different pixel intensity combinations within a specified neighborhood, providing valuable information about the visual characteristics of the vegetables. These texture features offer insights into the surface properties, patterns, and structures of the vegetables, enabling the system to distinguish between different quality categories.

d. Clustering:

After extracting the texture features, the system employs the K-Means clustering algorithm to group similar vegetable entries together. Clustering is a process of organizing data into groups or clusters based on their similarity. By clustering the vegetable entries, the system aims to identify common patterns and characteristics within each quality category (good, bad, and average). This step helps in creating distinct clusters for each quality category, enabling the subsequent classification phase to assign quality labels accurately.

e. Dataset Construction:

The clustering results serve as the basis for constructing a labeled dataset. Each vegetable entry is associated with a quality label (good, bad, or average) based on the clustering results. This labeled dataset is crucial for supervised learning during the classification phase. It forms the training data that the system will use to learn patterns and make predictions about the quality of new vegetable entries.

Testing Phase:

The testing phase focuses on classifying unlabeled vegetable entries and predicting their quality and estimated price. It involves the following steps:

a. Classification:

The testing phase starts with the classification of unlabeled vegetable entries. The K-Nearest Neighbors (KNN) algorithm is utilized for this task. KNN is a simple yet powerful algorithm that determines the class of a data point based on the classes of its nearest neighbors in the feature space. In the "Kisan to Kitchen" system, the KNN algorithm references the labeled dataset created during the training phase. By calculating the similarity between the unlabeled entries and the labeled samples, KNN assigns a quality category to each vegetable entry.

b. Quality & Price Prediction Estimation:

Once the quality category of each vegetable entry is determined through classification, the system proceeds with quality estimation and price prediction. A base price is fixed for each quality category (good, bad, and average). The system calculates the percentage of quality for each vegetable entry based on the extracted features. This percentage is used to adjust the base price, resulting in an estimated market value for the vegetable. The system presents these estimated prices to the farmers through the web portal, empowering them to negotiate fair prices and make informed decisions regarding their produce.

The "Kisan to Kitchen" system bridges the gap between traditional agricultural practices and technological advancements. By automating the process of vegetable quality assessment

## IV. RESULTS

| | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| 1 | Image | Entropy | Variance | Energy | Contrast | Homogeneity | Label |
| 2 | 1 | 6.512112 | 80.19226 | 0.013845 | 40.99926 | 0.001052433 | avg |
| 3 | 2 | 6.325226 | 32.48244 | 0.015681 | 40.31731 | 0.001085042 | good |
| 4 | 3 | 5.526068 | 39.61113 | 0.03228 | 34.40163 | 0.00103567 | good |
| 5 | 4 | 6.198557 | 44.63563 | 0.016773 | 43.62334 | 0.001160882 | avg |
| 6 | 5 | 6.327324 | 42.29674 | 0.014901 | 49.69035 | 0.001367446 | bad |
| 7 | 6 | 6.244639 | 32.37089 | 0.016539 | 43.10103 | 0.001067032 | good |
| 8 | 7 | 5.484195 | 41.87164 | 0.033229 | 34.76774 | 0.001040696 | good |
| 9 | 8 | 5.484195 | 41.87164 | 0.033229 | 34.76774 | 0.001040696 | good |
| 10 | 9 | 6.137339 | 171.3207 | 0.020376 | 32.98818 | 0.000958058 | avg |
| 11 | 10 | 6.300353 | 119.4523 | 0.016103 | 67.15858 | 0.001689268 | bad |
| 12 | 11 | 6.632793 | 42.7307 | 0.012477 | 40.84515 | 0.001056027 | avg |
| 13 | 12 | 8.9461 | 6070.992 | 0.004405 | 65.70407 | 0.60561964 | bad |
| 14 | 13 | 10.40923 | 3511.277 | 0.002407 | 61.5887 | 0.462304347 | avg |
| 15 | 14 | 9.589336 | 2575.212 | 0.002966 | 36.83026 | 0.458560695 | avg |
| 16 | 15 | 6.69254 | 4358.087 | 0.026814 | 46.11881 | 0.801532783 | bad |
| 17 | 16 | 8.446231 | 4473.588 | 0.006783 | 20.89431 | 0.718028445 | avg |
| 18 | 17 | 9.740305 | 4690.039 | 0.003329 | 115.3566 | 0.508865411 | avg |
| 19 | 18 | 8.354004 | 3002.109 | 0.005596 | 17.11423 | 0.739586991 | |
| 20 | 19 | 7.554708 | 3263.264 | 0.011594 | 14.61576 | 0.719490627 | |

Figure 4.1: Dataset before the quality checking

Figure 4.1 shows the dataset of carrots before the quality checking that is the data sample without labelling are present.

| | | | | | | |
|---|---|---|---|---|---|---|
| 16 | 8.446231 | 4473.588 | 0.006783 | 20.89431 | 0.718028 | avg |
| 17 | 9.740305 | 4690.039 | 0.003329 | 115.3566 | 0.508865 | avg |
| 18 | 8.354004 | 3002.109 | 0.005596 | 17.11423 | 0.739587 | avg |
| 19 | 7.554708 | 3263.264 | 0.011594 | 14.61576 | 0.719491 | avg |

Figure 4.2: Dataset after quality checking

Figure 4.2 shows the dataset after quality checking that is data sample with labeling using KNN classifier.

| 20 | Image | Entropy | Variance | Energy | Contrast | Homogeneity | Label | Distance | Quality | Cluster | Price |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 21 | 17 | 9.740305 | 4690.039 | 0.003329 | 115.3566 | 0.508865411 | avg | 0.45863 | 76.21938 | 1 | 57.16454 |
| 22 | 18 | 8.354004 | 3002.109 | 0.005596 | 17.11423 | 0.739586991 | avg | 0.299272 | 86.55927 | 2 | 64.91945 |
| 23 | 19 | 7.554708 | 3263.264 | 0.011594 | 14.61576 | 0.719490627 | avg | 0.145572 | 96.53208 | 2 | 72.39906 |

Figure 4.3: Distance, quality and cluster and the price calculated

Figure 4.3 depicts the estimated price of the test sample using distance estimations. Also, the record is highlighting the estimated quality of the carrot, cluster it belongs to and the estimated price of the carrot (test sample).

| Image | Entropy | Variance | Energy | Contrast | omogeneit | Label |
|---|---|---|---|---|---|---|
| 1 | 6.512112 | 80.19226 | 0.013845 | 40.99926 | 0.001052 | avg |
| 2 | 6.325226 | 32.48244 | 0.015681 | 40.31731 | 0.001085 | good |
| 3 | 5.526068 | 39.61113 | 0.03228 | 34.40163 | 0.001036 | good |
| 4 | 6.198557 | 44.63563 | 0.016773 | 43.62334 | 0.001161 | avg |
| 5 | 6.327324 | 42.29674 | 0.014901 | 49.69035 | 0.001367 | bad |
| 6 | 6.244639 | 32.37089 | 0.016539 | 43.10103 | 0.001067 | avg |
| 7 | 5.484195 | 41.87164 | 0.033229 | 34.76774 | 0.001041 | good |
| 8 | 5.484195 | 41.87164 | 0.033229 | 34.76774 | 0.001041 | good |
| 9 | 6.137339 | 171.3207 | 0.020376 | 32.98818 | 0.000958 | avg |
| 10 | 6.300353 | 119.4523 | 0.016103 | 67.15858 | 0.001689 | bad |
| 11 | 6.632793 | 42.7307 | 0.012477 | 40.84515 | 0.001056 | avg |
| 12 | 8.9461 | 6070.992 | 0.004405 | 65.70407 | 0.60562 | bad |
| 13 | 10.40923 | 3511.277 | 0.002407 | 61.5887 | 0.462304 | avg |
| 14 | 9.589336 | 2575.212 | 0.002966 | 36.83026 | 0.458561 | good |
| 15 | 6.69254 | 4358.087 | 0.026814 | 46.11881 | 0.801533 | bad |
| 16 | 8.446231 | 4473.588 | 0.006783 | 20.89431 | 0.718028 | avg |
| 17 | 9.740305 | 4690.039 | 0.003329 | 115.3566 | 0.508865 | avg |
| 18 | 8.354004 | 3002.109 | 0.005596 | 17.11423 | 0.739587 | avg |
| 19 | 7.554708 | 3263.264 | 0.011594 | 14.61576 | 0.719491 | avg |

Figure 4.4: Excel sheet results depicting the labelled carrot cross sections

Figure 4.4 shows the excel file screenshot of the labelled carrot cross sections.

| Image | Entropy | Variance | Energy | Contrast | omogeneit | Label | Distance | Quality | Cluster |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 6.512112 | 80.19226 | 0.013845 | 40.99926 | 0.001052 | avg | 0.227806 | 91.33351 | 0 |
| 2 | 6.325226 | 32.48244 | 0.015681 | 40.31731 | 0.001085 | good | 0.160839 | 95.61083 | 0 |
| 3 | 5.526068 | 39.61113 | 0.03228 | 34.40163 | 0.001036 | good | 0.401336 | 80.24966 | 0 |
| 4 | 6.198557 | 44.63563 | 0.016773 | 43.62334 | 0.001161 | avg | 0.121207 | 98.14223 | 0 |
| 5 | 6.327324 | 42.29674 | 0.014901 | 49.69035 | 0.001367 | bad | 0.198977 | 93.17489 | 0 |
| 6 | 6.244639 | 32.37089 | 0.016539 | 43.10103 | 0.001067 | avg | 0.129747 | 97.59678 | 0 |
| 7 | 5.484195 | 41.87164 | 0.033229 | 34.76774 | 0.001041 | good | 0.431622 | 78.31521 | 0 |
| 8 | 5.484195 | 41.87164 | 0.033229 | 34.76774 | 0.001041 | good | 0.431622 | 78.31521 | 0 |
| 9 | 6.137339 | 171.3207 | 0.020376 | 32.98818 | 0.000958 | avg | 0.092122 | 100 | 0 |
| 10 | 6.300353 | 119.4523 | 0.016103 | 67.15858 | 0.001689 | bad | 0.288665 | 87.44626 | 0 |
| 11 | 6.632793 | 42.7307 | 0.012477 | 40.84515 | 0.001056 | avg | 0.27748 | 88.1607 | 0 |
| 12 | 8.9461 | 6070.992 | 0.004405 | 65.70407 | 0.60562 | bad | 0.396015 | 80.58957 | 2 |
| 13 | 10.40923 | 3511.277 | 0.002407 | 61.5887 | 0.462304 | avg | 0.241004 | 90.49049 | 2 |
| 14 | 9.589336 | 2575.212 | 0.002966 | 36.83026 | 0.458561 | good | 0.49459 | 74.29326 | 2 |
| 15 | 6.69254 | 4358.087 | 0.026814 | 46.11881 | 0.801533 | bad | 0.61314 | 66.7212 | 1 |
| 16 | 8.446231 | 4473.588 | 0.006783 | 20.89431 | 0.718028 | avg | 0.235126 | 90.86595 | 1 |
| 17 | 9.740305 | 4690.039 | 0.003329 | 115.3566 | 0.508865 | avg | 0.380959 | 81.55121 | 2 |
| 18 | 8.354004 | 3002.109 | 0.005596 | 17.11423 | 0.739587 | avg | 0.237059 | 90.74245 | 1 |
| 19 | 7.554708 | 3263.264 | 0.011594 | 14.61576 | 0.719491 | avg | 0.126817 | 97.78396 | 1 |
| 20 | 9.740305 | 4690.039 | 0.003329 | 115.3566 | 0.508865 | avg | 0.380959 | 81.55121 | 2 |
| 21 | 8.354004 | 3002.109 | 0.005596 | 17.11423 | 0.739587 | avg | 0.237059 | 90.74245 | 1 |
| 22 | 10.36608 | 3781.215 | 0.001884 | 72.12236 | 0.471555 | avg | 0.157027 | 95.85435 | 2 |

Figure 4.5: Excel sheet results depicting the cluster, quality and distance vector of each of the carrot cross-sections.

Figure 4.5 shows the excel screenshot of the distance, quality clusters formed by the carrot cross-sections uploaded by the farmer.

| Image | Entropy | Variance | Energy | Contrast | omogeneit | Label | Distance | Quality | Cluster | Price |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 6.512112 | 80.19226 | 0.013845 | 40.99926 | 0.001052 | avg | 0.227806 | 91.33351 | 0 | 68.50013 |
| 2 | 6.325226 | 32.48244 | 0.015681 | 40.31731 | 0.001085 | good | 0.160839 | 95.61083 | 0 | 95.61083 |
| 3 | 5.526068 | 39.61113 | 0.03228 | 34.40163 | 0.001036 | good | 0.401336 | 80.24966 | 0 | 80.24966 |
| 4 | 6.198557 | 44.63563 | 0.016773 | 43.62334 | 0.001161 | avg | 0.121207 | 98.14223 | 0 | 73.60667 |
| 5 | 6.327324 | 42.29674 | 0.014901 | 49.69035 | 0.001367 | bad | 0.198977 | 93.17489 | 0 | 46.58744 |
| 6 | 6.244639 | 32.37089 | 0.016539 | 43.10103 | 0.001067 | avg | 0.129747 | 97.59678 | 0 | 73.19758 |
| 7 | 5.484195 | 41.87164 | 0.033229 | 34.76774 | 0.001041 | good | 0.431622 | 78.31521 | 0 | 78.31521 |
| 8 | 5.484195 | 41.87164 | 0.033229 | 34.76774 | 0.001041 | good | 0.431622 | 78.31521 | 0 | 78.31521 |
| 9 | 6.137339 | 171.3207 | 0.020376 | 32.98818 | 0.000958 | avg | 0.092122 | 100 | 0 | 75 |
| 10 | 6.300353 | 119.4523 | 0.016103 | 67.15858 | 0.001689 | bad | 0.288665 | 87.44626 | 0 | 43.72313 |
| 11 | 6.632793 | 42.7307 | 0.012477 | 40.84515 | 0.001056 | avg | 0.27748 | 88.1607 | 0 | 66.12053 |
| 12 | 8.9461 | 6070.992 | 0.004405 | 65.70407 | 0.60562 | bad | 0.396015 | 80.58957 | 2 | 40.29478 |
| 13 | 10.40923 | 3511.277 | 0.002407 | 61.5887 | 0.462304 | avg | 0.241004 | 90.49049 | 2 | 67.86787 |
| 14 | 9.589336 | 2575.212 | 0.002966 | 36.83026 | 0.458561 | good | 0.49459 | 74.29326 | 2 | 74.29326 |
| 15 | 6.69254 | 4358.087 | 0.026814 | 46.11881 | 0.801533 | bad | 0.61314 | 66.7212 | 1 | 33.3606 |
| 16 | 8.446231 | 4473.588 | 0.006783 | 20.89431 | 0.718028 | avg | 0.235126 | 90.86595 | 1 | 68.14946 |
| 17 | 9.740305 | 4690.039 | 0.003329 | 115.3566 | 0.508865 | avg | 0.380959 | 81.55121 | 2 | 61.16341 |
| 18 | 8.354004 | 3002.109 | 0.005596 | 17.11423 | 0.739587 | avg | 0.237059 | 90.74245 | 1 | 68.05684 |
| 19 | 7.554708 | 3263.264 | 0.011594 | 14.61576 | 0.719491 | avg | 0.126817 | 97.78396 | 1 | 73.33797 |
| 20 | 9.740305 | 4690.039 | 0.003329 | 115.3566 | 0.508865 | avg | 0.380959 | 81.55121 | 2 | 61.16341 |
| 21 | 8.354004 | 3002.109 | 0.005596 | 17.11423 | 0.739587 | avg | 0.237059 | 90.74245 | 1 | 68.05684 |
| 22 | 10.36608 | 3781.215 | 0.001884 | 72.12236 | 0.471555 | avg | 0.157027 | 95.85435 | 2 | 71.89076 |

Figure 4.6 Excel sheet results depicting the labelled carrot cross sections along with their prices.

Figure 4.6 shows the excel screenshot of the distance, quality clusters formed by the carrot cross-sections uploaded by the farmer along with the prices.

Figure 4.7: Carrot cross-section

Figure 4.7 shows the cross section of carrot image considered as the test sample for price estimation. The estimated / predicted price of the carrot based on the quality estimation is of Rs. 72.39/-

Figure 4.8: Carrot cross-section of good quality carrot

Figure 4.8 shows the carrot cross section of a good quality carrot which is uploaded by the farmer. Since the carrot quality is considered to be average, the price is estimated to be around Rs. 95/-

Figure 4.9: Carrot cross-section of an average quality carrot

Figure 4.9 shows the carrot cross section of an average quality carrot which is uploaded by the farmer. Since the carrot quality is considered to be average, the price is estimated to be around Rs. 65/-

Figure 4.10: Carrot cross-section of an average quality carrot

Figure 4.10 shows the carrot cross section of an average quality carrot which is uploaded by the farmer. Since the carrot quality is considered to be average, the price is estimated to be around Rs. 55/-

Figure 4.11: Carrot cross-section of a bad quality carrot

Figure 4.11 shows the carrot cross section of a good quality carrot which is uploaded by the farmer. Since the carrot quality is considered to be average, the price is estimated to be around Rs. 25/-

Figure 4.12: Carrot cross-section of a bad quality carrot

Figure 4.12 shows the carrot cross section of a good quality carrot which is uploaded by the farmer. Since the carrot quality is considered to be average, the price is estimated to be around Rs. 20/-

## V. CONCLUSION

The "Kisan to Kitchen" project has successfully developed a web portal that automates vegetable quality assessment and price estimation. By integrating image processing techniques and machine learning algorithms, the system accurately classifies vegetable images and determines their quality, allowing for the assignment of appropriate prices. The project combines data collection, preprocessing, feature extraction using the Gray-Level Co-occurrence Matrix (GLCM), and the application of clustering (K-Means) and classification (KNN) algorithms for accurate assessment. The web portal provides an easy-to-use interface for farmers to upload images, view quality assessments, and access estimated prices. This empowers farmers to make informed decisions and negotiate fair prices, improving market outcomes. The project contributes to market transparency, streamlines agricultural operations, and bridges the gap between traditional farming practices and technology. Further refinement and improvements are necessary to adapt the system to different vegetables and dynamic market conditions. Overall, the "Kisan to Kitchen" project represents a significant advancement in automating vegetable quality assessment and price estimation, revolutionizing the agricultural sector and empowering farmers with valuable information for profitable decision-making.

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