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ANALYZING MACHINE LEARNING METHODS TO ENHANCE GRAIN QUALITY ASSESSMENT AND EVOLUTION

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ABSTRACT

Assessing grain quality is a crucial component of agricultural production, with significant implications for global food security and economic prosperity. With the increasing demand for top-tier grains, there arises a pressing need for sophisticated methodologies to aid in the ongoing assessment and monitoring of grain quality throughout its development. This paper offers a comprehensive examination of machine learning (ML) techniques utilized in grain quality evaluation. Through an analysis of recent research advancements, methodologies, and practical applications, this review sheds light on the effectiveness and potential obstacles associated with ML-driven approaches for enhancing grain quality assessment. Key areas of focus include the deployment of ML algorithms for predicting, classifying, and monitoring grain quality, as well as the incorporation of advanced sensing technologies and data analytics into grain quality assessment systems. Additionally, the review delves into emerging trends, future research avenues, and the broader implications of ML techniques in streamlining grain production processes and ensuring food safety and sustainability. By conducting a systematic review of existing literature, this paper contributes to a deeper comprehension of the role played by ML in addressing the multifaceted challenges of grain quality assessment and management within contemporary agriculture.

Keywords: Machine vision; Wheat; Seed quality; Classification; Quality; Deep Learning.

1. INTRODUCTION

Mobile grains represent the seeds harvested from various grasses like wheat, oats, corn, rice, millet, rye, and barley, serving as essential sources of nutrition. Cereals fulfill a significant role in meeting human dietary requirements, with grains contributing approximately 48% of total calorie intake. Grain quality is a crucial determinant for market acceptance, influencing pricing and quality indices tailored to specific end-use requirements. Quality assessment in grain processing units relies on physical characteristics such as firmness, shape, moisture content, and size, and visual attributes like damage, infection, and discoloration, ensuring grains are free from contaminants harmful to health. Traditional methods of quality assessment, particularly visual inspection, are quick and reliable but pose challenges in accuracy, often influenced by market sentiments, leading to discrepancies in pricing and unfair outcomes for farmers.

Wheat, a widely consumed cereal grain, comprises three main components: bran, germ, and endosperm. Bran, the outer layer of wheat grains, contains fiber, vitamins, and minerals, while the germ serves as the embryo rich in essential nutrients. The endosperm, the largest part of the wheat kernel, contains starch and protein. Wheat-based products encompass a diverse range of foods such as bread, pasta, noodles, cereals, and baked goods. The nutritional value and texture of the final product are influenced by the type of wheat used and the processing method, with whole grain products retaining more fiber and nutrients compared to refined wheat products lacking bran and germ components.

Computer Vision System CVS) represents a transformative technology that has revolutionized various industries by enabling machines to perceive, interpret, and understand visual information. With roots in artificial intelligence and image processing, computer vision systems have emerged as powerful tools for automating tasks that were once exclusive to human perception. By harnessing the capabilities of digital cameras, sensors, and sophisticated algorithms, CVS can analyze and extract meaningful insights from images and video data in real-time.

The evolution of computer vision systems has been propelled by advancements in hardware technology, such as high-resolution cameras, GPUs, and specialized processors, which have exponentially increased processing power and enabled the execution of complex algorithms with remarkable speed and efficiency. Additionally, the development of deep learning algorithms, particularly convolutional neural networks (CNNs), has significantly enhanced the performance of computer vision systems by enabling them to learn intricate patterns and features from large datasets **(Waoo and Soni 2023).**

In diverse fields ranging from healthcare and automotive to agriculture and manufacturing, computer vision systems are being deployed for a myriad of applications. In healthcare, CVS aids in medical image analysis, disease diagnosis, and surgical assistance, improving patient outcomes and streamlining clinical workflows. In the automotive industry, computer vision systems power autonomous vehicles, enabling them to perceive and navigate their surroundings, enhancing safety and efficiency on the roads.

Moreover, in agriculture, CVS facilitates crop monitoring, disease detection, and yield prediction, empowering farmers with actionable insights to optimize farming practices and increase productivity. In manufacturing, computer vision systems enable quality control, defect detection, and object recognition, ensuring product consistency and minimizing defects.

Despite the remarkable progress made in the field of computer vision, challenges remain, including issues related to data privacy, algorithm bias, and ethical considerations. As computer vision systems continue to evolve, it is essential to address these challenges while maximizing the potential benefits of this transformative technology.

In this comprehensive guide to computer vision systems, we will delve into the fundamental principles, methodologies, applications, and future directions of CVS. Through a systematic exploration of key concepts and real-world case studies, readers will gain a deeper understanding of how computer vision systems are reshaping industries and driving innovation in the digital age.

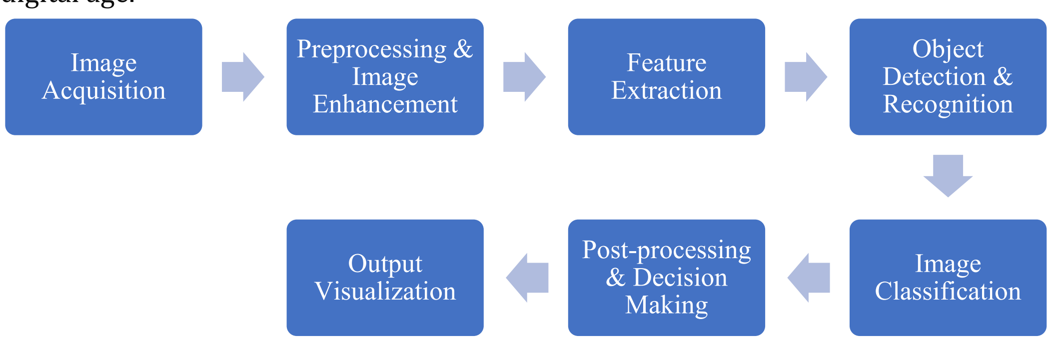


Fig 1: Block diagram for Computer Vision System

Fig 1 diagram illustrates the standard process flow of a Computer Vision System, commencing with the acquisition of images via a digital camera or sensor. Subsequently, the obtained images undergo preprocessing and enhancement procedures to enhance their quality and clarity. Following this, feature extraction methods, such as Convolutional Neural Networks (CNNs) or feature descriptors, are employed to discern pertinent features within the images. Afterward, object detection and recognition algorithms are utilized to pinpoint and identify objects present in the images. Once objects are identified and recognized, image classification algorithms, frequently leveraging machine learning techniques, categorize the objects into predefined classes. Subsequent steps involve post-processing and decision-making based on the classification outcomes, potentially leading to further analysis or actions based on the identified objects. Ultimately, the Computer Vision System's output is presented visually, either through a display for human interpretation or through data transmission for additional processing or storage purposes.

2. WHEAT GRAIN STRUCTURE

The structure of wheat grains comprises the endosperm, a central white powder within the grain, which separates from the bran layer upon crushing. **(Solah et. al. 2015)** The ease of separation depends on wheat properties, with durum wheat separating easily for bread-making, while soft wheat used in biscuit flour does not separate cleanly. Bran, rich in protein, is utilized in producing brown and whole wheat flour. The wheat germ, containing vitamins, proteins, and oils, develops into the wheat plant and is commonly used in healthy foods like fortified bread.

Regarding grain quality parameters, wheat quality is categorized into species, varieties, and physical and chemical properties. Physical attributes include grain weight, firmness, size **(Tanabata et. al. 2012),** shape, virtue, and color, with wheat test weight being a common and convenient measure, indicating flour production estimate. Factors influencing test weight include grain size, shape, density, and maturity. Wheat endosperm hardness is vital for determining suitability for different end products and affects processing and milling. It's a key factor in wheat grading used by millers and traders, dividing wheat into durum and soft wheat based on hardness. Wheat is also classified by color into red and white classes, with various uses like breadcrumbs, pastries, and pasta. Different types of wheat exhibit distinct characteristics such as flavor, unit, and milled yield. Wheat vitreousness, an optical property, classifies wheat into glassy, powdery, and mottled categories, with glass wheat considered superior due to its high-quality semolina protein, attractive color, and consistent coarse grain.

The shape of grains is a significant characteristic determined primarily by the aspect ratio, defined as the ratio of the length to the width of the grain. **(Kaspar et. al. 2004)** The aspect ratio is the ratio of the length of the seed to the ratio of the width of the seed. The aspect ratio (AR) formula is given by:

$$\boxed{\textbf{Aspect Ratio} = \mathbf{L / W}}$$

Where:
L: Length of the kernel
W: Width of the kernel

For any grain sample, generally, the average value is considered:

$$\boxed{\textbf{Aspect Ratio}_{\mathbf{(avg)}} = \mathbf{L_{avg} / W_{avg}}}$$

Where:
L_{avg}: The average length of the kernel
W_{avg}: The average width of the kernel

The aspect ratio, typically measured in millimeters, serves as a basis for seed classification, determined by the ratio of seed length to width. Product appearance often hinges on this aspect ratio, which can significantly impact sales. Consumers are selective, and despite a product's nutritional value, its attractiveness plays a crucial role in consumer purchasing decisions. Moreover, uniformity in length and width is essential, as samples with consistent dimensions often command a price premium due to their visual appeal.

3. DAMAGED / DISCOLORED GRAINS

Spoiled grains, characterized by altered appearance and diminished nutritional value due to biochemical changes, result in unusual flavors and visual discrepancies. Factors such as moisture levels, pest infestation, physical trauma, insect activity, and exposure to heat contribute to this type of damage. Damaged or discolored kernels encompass various abnormalities, including fractures, internal defects, discoloration, and immature or abnormal coloring like yellow, red, or green hues. It can be measured as:

% Damaged grain = (Total damaged seed / Total seeds) X 100

Assessment of grain weight offers insights into grain size and density, which influence grinding methods, moisture retention, and cooking properties. Consistency in grain weight is crucial for maintaining uniform grain quality, as even seemingly identical samples may differ in weight, impacting processing outcomes.

4. LITERATURE SURVEY

Manual Grain Analysis Technique In manual grain analysis, grain samples are examined visually, often using tools like micrometers and Vernier calipers to measure various dimensions. However, the outcomes of such assessments are largely subjective and heavily reliant on the skills and mindset of the analyst. Even with the same sample and analyst, repeated measurements may yield inconsistent results, reducing the reliability of the findings. Moreover, manual measurement of individual seed parameters is time-consuming and challenging, making it difficult to accurately assess quality attributes and remember the characteristics of each seed. Typically, average characteristics such as length, width, color, and the presence of broken seeds are determined through this method, but there's a risk of physical damage or distortion. Analyzing numerous samples further complicates the process, and inexperienced analysts may produce inaccurate results. Overall, manual analysis is highly influenced by human factors and environmental conditions, introducing potential errors into the analysis.

Semi-automatic particle analysis methods, such as sieve analysis **(Enebe et. al. 2013)**, are employed to segment particulate matter into various size fractions and ascertain the weight of each fraction. In this approach, the sample is introduced into a sieve tower, as depicted. The base of the tower features a mechanical shaker, as illustrated in Figure [3]. In standard sieving procedures, a sequence of sieves with varying aperture sizes separates the seeds into distinct size groups at each tier, with each tier progressively resizing the particles.

Manual and Mechanical Screening The manual screening method operates without a power source, relying instead on mechanical energy generated by the sieve. Screens are categorized into throwing screens and horizontal screens based on their rotational direction.

Single sieve and sieve set sieves are solely employed to determine the percentages of undersized and oversized particles and are not suited for assessing particle size distribution comprehensively. In individual screening, a single screen with a specified mesh size is utilized along with a collection pan. However, this method is merely indicative, as particles of varying sizes may be present at each stage. While the sieving technique can be useful for determining corn particle size, its accuracy is compromised as grain seeds may pass through vertically. This method is typically effective for round or nearly round seeds and is commonly employed in particle size analysis, lacking information on other properties like aspect ratio or color.

In recent years, image-based particle analysis has gained traction, with various techniques developed. This approach utilizes captured images of particles to conduct comprehensive parametric analyses. The subsequent section will outline diverse image processing-based techniques for particle analysis.

Fig 2: Sieves sets

Fig 3: Sieve shaker

Traditional Methods of Image-based Particle Analysis have undergone significant advancements due to recent technological progress in the field of image processing, establishing it as a versatile and widely accepted technique for extracting features in particle quality analysis. In image-based grain analysis, grain kernels are either arranged on grain trays or conveyed via conveyor belts, and images of grain samples are obtained through scanning with scanners or captured using various types of cameras. These captured images are then subjected to preprocessing to enhance their quality before feature extraction for each seed. Sorting based on the extracted features of each seed in the grain sample image is then performed. Image-based particle analyzers are generally categorized into two types:

1. Offline Grain Analyzers
2. Online Grain Analyzers.

Both techniques bring in an image of the wood grain pattern for processing. In the online grain analyzer **(Dudhrejia et. al. 2017)** the grain moves while taking a picture of the grain sample. With offline grain analyzers, the grain remains stable while the grain sample is photographed.

Machine getting-to-know strategies had formerly been efficiently carried out in lots of manufacturing chains for the seed and cereals category [**(Agrawal et. al. 2021)**, **(Rieder et. al. (2018)**, and **(Moses et. al. 2016)**]. The **(Du et. al. 2006)** study suggests the functionality and opportunities of system imaginative and prescient for shapes, sizes, and varietal kinds of the use of well-skilled multilayer neural community classifiers. They applied Weka class gear which includes function, Bayes, Meta, and lazy processes to categorize the seeds. In **(T. Tujo 2019)**, the authors proposed a fuzzy theory primarily based on the total technique for spotting wheat seed kinds that recall the capabilities of the seed. The tabu seeks method changed into used. In **(Liu et. al. 2012)**, the authors used a synthetic neural community for classifying wheat seeds primarily based totally on VLC and acquired an accuracy of 92.1 percent and 85. Seventy-two percent, respectively. In **(Paliwal et. al. 2009)**, the authors mentioned the morphological, color, and textural traits of the seed. If there's a completely minute distinction in morphological capabilities, then seed class could be very difficult. Cereal yield is decided via way of means of the number of grains consistent with the ear and the dimensions of the grains. Counting seeds and morphometry via way of means of sight is time-consuming. As a result, distinctive methods for powerful grain morphometry using photograph processing strategies have been proposed [**(White et. al. 2003)**, **(Tanabata et. al. 2012)**].

In **(Komyshev et. al. 2017)**, the authors created a computer to resource in grain evaluation for class, and a video colorimetry technique was offered to aid in figuring out cereal grain color. The categorization of chickpea seed types changed accomplished primarily based totally on the morphological traits of chickpea seeds, the use of four hundred samples from 4 kinds: Kaka, Piroz, Ilc, and Jam **(Neuman et. al. 1989)**. According to the industrial factor of view, a system imaginative and prescient constructed of present neural community fashions can be applied for rice first-rate assessment **(Ghamari 2012)**. In this, it makes use of neural networks to categorize rice types, the use of a complete of 9 separate styles of rice. The authors appoint seed photograph acquisition to categorize those variations. They additionally created a technique for extracting thirteen morphological capabilities, 6 color capabilities, and 15 texture capabilities from color pics of seeds. Their version has produced an average class accuracy of 92%. The k-nearest acquaintances classifier necessitates storing the whole education set, which may be prohibitively luxurious whilst the set is huge, and numerous researchers have tried to get rid of the education setting's redundancy to alleviate this hassle **[(Silva et. al. 2013), (Kubat et. al. 2000)].**

For plant categorization, the authors have applied deep getting-to-know fashions. Two inclinations can be visible inside the contemporary country of art. The first is connected to high-throughput phenotyping and plant identity, as evidenced by Ubbens and Stavness' paintings on this area. The 2nd hassle is plant ailment identity and monitoring. **(Ferentinos 2018)** authors gift many balloting strategies for trying out ensembles of classifiers and discovered the use of the bagging technique. The multilayer perceptron is used as a classifier. Using agencies of classifiers instead of personal ones is one option. Bagging and boosting are the maximum famous ensemble strategies, wherein many classifiers are mixed to generate a single, extra correct result. **(Singer et. al. 1998)** authors studied the overall performance of numerous balloting strategies, with bagging being applied for the reconciliation version which is a method of merging class fashions.

Zayas et al. 1989 illustrate the use of image analysis to distinguish between wheat and non-wheat components in a grain sample. They presented two methods, a multivariate discriminant method and a structural prototype method for pattern recognition. The main concern with this method misclassification of irregularly shaped stones such as wheat. The limitation of the proposed method is the need to manually orient the kernel. Grain per cob and grain size are important characteristics of grain yield. Counting seeds and morphology "by eye" is laborious. Therefore, many different approaches have been proposed for efficient particle morphology measurement by image processing techniques [3], [18]. Classification testing was performed through non-destructive analysis and classification methods of particle characteristics [51], [52]. Machine learning is often used in various applications such as classification, regression, and forecasting to meet these needs **(Agrawal et. al. 2021).**

Vishnu et al. 2017 Proposed a technique based on PCA and K-mean cluster analysis also presented for the quality analysis of rice bran collected from rice mills. Based on oil contents, there are different types of rice bran e.g., the oil contents of boiled rice bran range from (20~26%), and oil contents for raw rice bran range from (16~18%).

Parveen et al. 2017 Presented Optimal and image processing-based techniques for the characterization and quality analysis of rice grains based on the chalky white part of rice grain. A white chalky area of grains is detected using an extended maxima operator.

Ahmad et al. 2007 Present color machine vision systems that have been used in grain quality analysis to distinguish between seeds, grades, varieties, impurities, and seeds contaminated with fungi and insects. The color image of each grain is described by its color, texture, and morphological characteristics and is used in the assessment of grain quality.. **Gowen et al. 2010** Proposed thermal imaging systems, which use thermal IR radiation detectors (long-wave), have also been investigated for their applications in the quality and safety inspection of agricultural and food products.

Momin et al. 2017 Presented the detection of Materials Other than Grain in soybean harvesting successfully identified with an accuracy of 96% for split beans, 75% for contaminated beans, and 98% for both defective beans and stem/pods.

Aran et al. 2017 Implement an automated grading system using machine vision which takes the Cashew input image processes it and transfers it to a pattern recognizer. The pattern recognizer performs processing and classifies the object. Grading is performed using color, texture, size, and shape features. Five different classifiers were used among these classifiers Back Propagation neural network proved more optimal.

R. Siddagangappa et al. 2014 propose an automated system for classification and quality determination using a neural network. The proposed model uses color and geometrical features for classification. The success rate for identification was 98% and the success rate of quality analysis and grading of rice grain was 90% and 92%.

H. S. H. Chitra et al. 2016 proposed a methodology for the identification and classification of seeds. By using this technology, the author can discriminate the defective seed from the normal seed. The proposed methodology includes noise removal, edge detection, segmentation, and classification for seed identification.

Bejo et al. 2017 combined two non-destructive sensors to predict the sugar content of mango sweetness. A spectrophotometer and computer vision system implemented online resulted in an accuracy of 87% for the prediction of sugar content.

Radhika V. Rao et al. 2014 proposed an algorithm for determining the protein content of the seed using a machine learning algorithm.

Zareiforoush H et al. 2015 Proposed an algorithm based on the nearest neighbor approach, MLP, and support vector machine method which provides higher classification accuracy. Quality measurement of milled rice grading developed by fuzzy inference system combined with image processing to give qualitative decision support system.

Singh CB et al. 2010 proposed an Image analysis technique for both the identification and classification of the materials and used to detect the infestation seed materials infestation inside the wheat kernels using thermal imaging.

Tajane et al. 2014 developed techniques that work on Ayurvedic Plant leaf detection by image analysis technique.

Ribeiro 2016 proposed an approach to classify five cereals, extracting morphological, color, and texture characteristics. To increase classification accuracy, the original RGB color space is converted to HSV color for best results.
Komyshev et al. 2017 proposed an approach to evaluate the phenotypic parameters of the grains using mobile devices obtaining quite precise results.

Kaisaat et al. 2017 proposed a flat-surface scanner to measure the color of the rice and its corresponding uniformity.

Fernandez-Gallego et al. 2018 proposed a robust, inexpensive, and effective method to evaluate the density of wheat ears in the visible spectrum. Also, focus on using inexpensive and readily available equipment.

Huang et. al 2019, Wah et al. 2018, Birla et. al. 2015, and **Minaei et. al. 2015** proposed converting the given images to grayscale and using them as inputs to the system. When working in grayscale, just one dimension is considered, hence in these cases the texture or intensity analysis is considered.

Sendin et. al. 2019, Singh et al. 2016, and Olgun et. al. 2016 proposed a classification directly from the given images, this breakdown is useful to cluster the approaches in the literature for further analysis and comparisons.

Kozłowski et al. 2019 propose a flatbed scanner to acquire images and perform recognition of barley varieties.

Kar et al. 2019 proposed a deep learning-based system to estimate food grain quality using a mobile device with limited resources.

Gomez et al. 2019 proposed an approach to classify cocoa beans, based on the spectral signatures of the visible and near-infrared spectral bands.

Kar et al. 2019 perform the classification of wheat grains by using a hybrid strategy where real images are used in a virtual environment for training the instance segmentation architecture.

Singh and Chaudhury et al. 2020 present an approach to classify five types of rice, using a vector of characteristics applying the BPNN algorithm using the luminance component of the converted HSV color spaces.

Chu et al. 2020 proposed an approach to classify infected corn seeds is proposed. It uses infrared hyperspectral images in the range of 900 to 1700 nm.

Toda et al. 2020 proposed a deep learning-based grain detection method to identify seeds of various types, for example, barley, rice, lettuce, oats, and wheat.

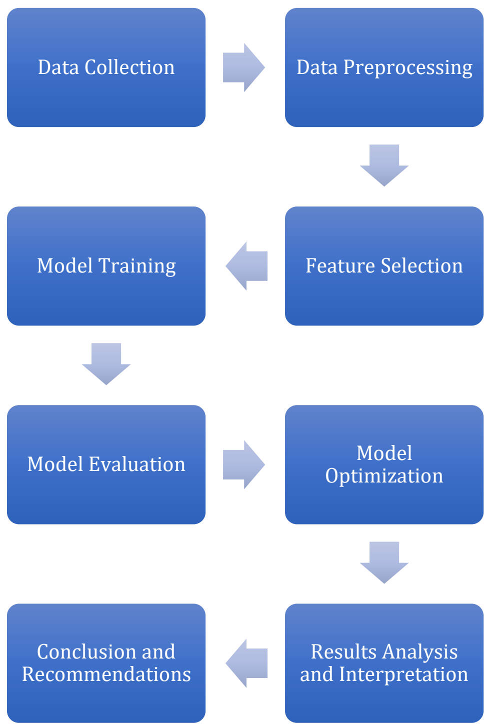
UCI Machine Learning Repository 2021, **P. Hart 1968**, **G. Gates 1972**, and **E. Alpaydin 1997** K-Nearest-Neighbours classifier requires storing the whole training set and may be too costly when this set is large, many researchers have attempted to get rid of the redundancy of the training set to alleviate this problem.

Aznan et al. 2021 proposed an application of computer vision (CV) and machine learning (ML) to classify commercial rice samples based on dimensionless morphometric parameters and color parameters extracted using CV algorithms from digital images obtained from a smartphone camera.

5. RESEARCH METHODOLOGY

Research Methodology for Machine Learning Methods to Enhance Grain Quality Assessment and Evolution

- **Define Research Objectives:** Clearly outline the objectives of the study, which include assessing the effectiveness of machine learning methods in enhancing grain quality assessment and understanding the evolutionary trends in grain quality over time.
- **Literature Review:** Conduct a thorough review of existing literature on machine learning techniques applied to grain quality assessment and evolution. Identify gaps in knowledge and areas for further investigation.
- **Selection of Machine Learning Methods:** Identify and select appropriate machine learning algorithms and techniques suitable for analyzing grain-quality data. Consider factors such as data complexity, model interpretability, and computational efficiency.
- **Data Collection:** Gather relevant datasets containing information on grain quality parameters such as moisture content, protein content, starch content, and physical attributes. Ensure the datasets cover a diverse range of grains and geographical locations to capture variations in grain quality.



Fig

6. RESEARCH METHODOLOGY BLOCK DIAGRAM

- **Data Preprocessing:** Clean and preprocess the collected data to address issues such as missing values, outliers, and inconsistencies. Normalize or scale the data to ensure uniformity and improve the performance of machine learning models.
- **Feature Selection and Engineering:** Identify relevant features that contribute to grain quality assessment and evolution. Conduct feature selection and engineering techniques to enhance the predictive power of machine learning models.
- **Model Development and Evaluation:** Develop machine learning models, including supervised learning algorithms (e.g., regression, classification) and unsupervised learning techniques (e.g., clustering), to analyze grain quality data. Train the models using the pre-processed data and evaluate their performance using appropriate metrics such as accuracy, precision, recall, and F1-score.
- **Comparison of Methods:** Compare the performance of different machine learning methods in terms of their ability to assess grain quality and identify evolutionary trends. Assess the strengths and limitations of each approach and identify the most effective methods for grain quality analysis.

- **Interpretation of Results:** Interpret the findings of the machine learning analysis in the context of grain quality assessment and evolution. Identify patterns, trends, and insights gleaned from the data and discuss their implications for agricultural practices and food production.
- **Validation and Robustness Testing:** Validate the results of the machine learning analysis using cross-validation techniques and sensitivity analysis. Ensure that the findings are robust and generalize well to different datasets and scenarios.
- **Ethical Considerations:** Consider ethical issues related to data privacy, consent, and bias in the machine learning analysis. Ensure that the research adheres to ethical standards and guidelines.
- **Documentation and Reporting:** Document the research methodology, data sources, and analysis procedures in detail. Prepare a comprehensive report summarizing the research findings, methodology, and implications for stakeholders in the agricultural industry.

7. CONCLUSION

The research has provided valuable insights into the potential applications of advanced technologies in the agricultural sector. Through rigorous data collection, preprocessing, and model training, various machine learning algorithms were evaluated for their effectiveness in assessing grain quality parameters.

The results obtained from the study indicate that machine learning methods have the potential to significantly enhance grain quality assessment processes, offering more accurate and efficient alternatives to traditional methods. By leveraging these technologies, stakeholders in the agricultural industry can streamline production processes, optimize resource allocation, and improve overall grain quality.

Furthermore, the research highlights the importance of ongoing optimization and refinement of machine learning models to ensure their relevance and effectiveness in real-world scenarios. As technology continues to advance, further research and development in this field are warranted to unlock the full potential of machine learning in enhancing grain quality assessment and supporting sustainable agricultural practices.

In summary, the findings of this study underscore the transformative impact of machine learning on grain quality assessment and its evolution, paving the way for innovative solutions to address the challenges faced by the agricultural industry in the 21st century.

CONFLICT OF INTERESTS

None.

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