The Computer Vision and Type-II Fuzzy Logic based Hybrid Intelligent Approach for Quality Measurement of Wheat Crop

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ABSTRACT
In the proposed research, a fuzzy inference system (FIS) coupled with image processing approach has been developed as a decision support system (DSS) for grading the quality of wheat crop. Degree of milling (DDM) and percentage of broken kernels (PBK) quality indices has been graded by the wheat crop experts into five classes. Wheat is one of the most significant cereal crops worldwide and plays a vital role in global food security and agricultural economics. Traditional wheat quality assessment methods are generally manual, time-consuming, subjective, and prone to human error. Recent developments in computer vision, artificial intelligence, and fuzzy logic have enabled automated and intelligent grain quality inspection systems. This research paper proposes a hybrid intelligent framework integrating computer vision techniques with Type-II Fuzzy Logic for efficient and accurate quality measurement of wheat crops. The proposed approach combines image acquisition, preprocessing, feature extraction, classification, and fuzzy inference mechanisms to evaluate wheat grain quality based on parameters such as size, shape, color, texture, impurities, and damage level. The integration of Type-II fuzzy systems helps address uncertainty and ambiguity present in real-world agricultural environments. Experimental analysis demonstrates that the hybrid model significantly improves classification accuracy, robustness, and decision-making capability compared to conventional methods.

Keywords
Computer Vision, Type-II Fuzzy Logic, Wheat Quality Assessment, Hybrid Intelligent System, Image Processing

1. INTRODUCTION
Wheat is grown on 13% of the cropped area of India. Next to rice, wheat is the most important food-grain of India and is the staple food of millions of Indians, particularly in the northern and north-western parts of the country. India produces 08 % of world's total production. India is the fourth largest producer of wheat in the world after Russia, the USA and China. Wheat is a major crop of India, mainly yield in the winter season [1]. With the continued population growth, the food industry needs to keep increasing production and improving the quality of products. Directly or indirectly related to the increase in food production are the cereals, which are at the base of the pyramid of the food industry, both for human and animal consumption.

Wheat is one of the important staple cereal food crops of India and accounts for 35% of the food grain production of the country. Its grains are comparatively better source of protein than other cereals. Recently during 2017-18 in Punjab the area under wheat cultivation was 3.5 million hectares with production of 17.82 million tons [2]. Since wheat is a winter season crop and hence is more vulnerable to high temperature conditions. Hundal [3] reported that an increase in temperature by 1oC from normal decreases the wheat yield by 10% under Punjab conditions.

The actual and potential yield of wheat may decline by 38 and 50%, respectively with 5oCbincrease in temperature [4, 5] reported that during post-anthesis period in wheat an exposure to continual minimum temperature 12oC for 6 days and maximum temperature 34oC for 7bdays are the main thermal constraints in achieving high productivity. Among production factors of wheat, sowing time and varieties are the most crucial factors deciding its productivity. Sowing of wheat generally starts from November and ends in late December depending on the weather; topography and harvesting of the preceding crop. Under late sown conditions, wheat face low temperature in the earlier part and high temperature in the later part of the growing season.

According to the United Nations' Food and Agriculture Organization (FAO), food production would need to increase by 50 % by 2050 to satisfy the world's growing population. Climate change has an impact on the production of key crops in the current situation (WHO2018). As a result, understanding the precise condition of crop yield variability and availability makes it difficult to not only correctly forecast agricultural fields, but also to model and plan the processes involved.

The FAO report shows that the increase in production has kept the same ratio during the last decade and it is expected to keep the same ratio in the near future. Therefore, since it is difficult to increase the arable land, improvements are required in other processes in the production chain to increase productivity. One of these improvements is related to the automation of the classification of food grains, where a great effort has been devoted in recent years by proposing new approaches to perform the classification in an automatic way. It should be noticed that the food grain classification problem requires specific features according to the type of variety or problem. Some classes (seeds) have a large inter-class variability making easier the solution while others show a very tiny inter-class variability (e.g., classify between good grain and infected one). Actually, some of these challenging problems (small inter-class variability) requires the usage of multispectral or hyperspectral technology. [1,7].

2. LITERATURE REVIEW
Several researchers have explored computer vision and

machine learning methods for grain quality evaluation. Recent studies have demonstrated the effectiveness of convolutional neural networks (CNNs) and intelligent image analysis systems for wheat appearance assessment. An intelligent wheat quality detection system developed using multi-grained convolutional neural networks achieved an accuracy of 99.45% in wheat grain classification.

Research on image processing techniques for wheat grain inspection has shown that morphological and texture features can effectively classify damaged and healthy wheat kernels. Machine learning approaches have also been applied to automate wheat grain classification and impurity detection. Fuzzy logic has been widely used in intelligent agricultural systems because of its ability to mimic human reasoning under uncertain conditions. Studies on machine vision and fuzzy logic integration in grain processing systems demonstrated improved decision-making performance in quality evaluation applications.

Recent reviews on fuzzy theory in computer vision emphasize the importance of Type-II fuzzy systems in handling image uncertainty, noise, and vague boundaries in classification tasks. Although significant work has been carried out separately in computer vision and fuzzy systems, limited research has focused on integrating Type-II fuzzy logic with computer vision for wheat crop quality measurement. Therefore, this research addresses this gap through a hybrid intelligent framework.

Agriculture remains the backbone of many economies, particularly in developing countries where wheat serves as a staple food crop. Accurate assessment of wheat quality is essential for pricing, storage, transportation, food processing, and export standards. Conventional wheat quality measurement relies heavily on human experts who visually inspect grains for defects, discoloration, broken kernels, fungal infection, and impurities. However, manual inspection methods are subjective, labor-intensive, inconsistent, and unsuitable for large-scale operations.

Advancements in computer vision and artificial intelligence have introduced automated approaches for agricultural inspection systems. Computer vision technologies enable machines to analyze digital images and extract meaningful features from grain samples. Deep learning and image processing techniques have shown promising results in grain classification and defect detection. Fuzzy logic has emerged as an effective method for handling uncertain and imprecise information in agricultural systems. In particular, Type-II Fuzzy Logic Systems (T2FLS) provide enhanced capability in modelling uncertainty compared to traditional Type-I fuzzy systems. Type-II fuzzy systems are highly suitable for agricultural image analysis because environmental conditions such as illumination, grain orientation, sensor noise, and texture variations introduce ambiguity into the data.

This paper presents a hybrid intelligent approach combining computer vision and Type-II fuzzy logic for wheat quality measurement. The proposed system aims to improve the reliability, accuracy, and adaptability of wheat quality inspection systems under real-world agricultural conditions.

Objectives of the Study

The major objectives of this research are:

1. To develop an automated wheat quality assessment system using computer vision techniques.
2. To extract significant visual features such as color, texture, shape, and size from wheat grain images.
3. To design a Type-II fuzzy inference system for handling uncertainty in grain quality evaluation.
4. To integrate computer vision and fuzzy logic into a hybrid intelligent framework.
5. To improve the accuracy and robustness of wheat quality classification.

3. FUZZY INFERENCE SYSTEM

A Fuzzy Inference System (FIS) is a computing framework tthat maps input data to output decisions using fuzzy set theory and human-like "if-then" rules rather than exact Boolean logic. It enables computers to process imprecise, linguistic variables (e.g., "if temperature is high, then fan speed is fast"), making it crucial for control systems, expert systems, and decision-making.

Fuzzy inference systems are particularly useful when an exact mathematical model of a system is difficult to formulate, providing a non-linear mapping that is easily interpretable. Fuzzy Inference Process

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves all the pieces that are described in Membership Functions, Logical Operations, and If-Then Rules.

The fuzzy inference system (FIS) was implemented in the fuzzy toolbox of MATLAB 2013a. The first step in each FIS implementation is to define the name and number of the variables involved in the inference and decision-making process. These parameters are initially in the form of crisp (0 and 1) variables, which are then converted to fuzzy rules using the fuzzifier functions.

4. PROPOSED HYBRID INTELLIGENT FRAMEWORK

The proposed framework consists of five major stages:

- Image Acquisition
- Image Preprocessing
- Feature Extraction
- Type-II Fuzzy Inference System
- Wheat Quality Classification

4.1 Image Acquisition

High-resolution digital cameras or smartphone imaging systems are used to capture wheat grain images under controlled lighting conditions. Images are collected from different wheat categories including: Healthy grains, Broken grains, Shriveled grains, Diseased grains, Impure grains. The image database contains multiple samples with variations in orientation, illumination, and background conditions.

4.2 Image Preprocessing

Preprocessing enhances image quality and removes noise before feature extraction. The following techniques are applied: RGB to grayscale conversion, Histogram equalization, Median filtering, Contrast enhancement, Image segmentation, Background removal. Thresholding and edge detection techniques are used to isolate wheat kernels from the background.

4.3 Feature Extraction

Feature extraction is one of the most important stages in wheat quality analysis. The system extracts several visual attributes from grain images.

4.3.1. Color Features

Color characteristics help identify diseased and discolored grains. Features include: Mean RGB valuesm HSV color components, Color histogram distribution.

4.3.2. Shape Features

Shape analysis identifies broken or shriveled grains using: Area, Perimeter, Circularity, Aspect ratio, Compactness

4.3.3. Texture Features

Texture analysis is performed using Gray-Level Co-occurrence Matrix (GLCM) techniques. The extracted texture parameters include: Contrast, Correlation, Energy, Homogeneity, Entropy.

4.3.4. Size Features

Kernel dimensions are measured using image morphology operations: Length, Width, Diameter, Kernel volume estimation. Studies have shown that image processing techniques effectively estimate wheat morphological characteristics and physical quality indicators.

5. TYPE-II FUZZY INFERENCE SYSTEM

A Type-II Fuzzy Inference System (Type-II FIS) is an advanced fuzzy logic framework that models uncertainty more effectively than a traditional Type-I Fuzzy Inference System. It is particularly suitable for applications where data are noisy, imprecise, or influenced by expert judgment, such as medical diagnosis, autonomous systems, and agricultural quality assessment.

Mathematical Representation of Type-II FIS

For a Type-I fuzzy set:

$$A = \{(x, \mu_A(x))\}$$

Where,

$$\mu_A(x) \in [0,1]$$

For a Type-II fuzzy set:

$$\tilde{A} = \{((x, u), \mu_{\tilde{A}}(x, u))\}$$

Where,

x= primary variable

u= secondary membership

$$\mu_{\tilde{A}}(x, u) \in [0,1]$$

The uncertainty between the upper and lower membership functions is called the Footprint of Uncertainty (FOU).

Compared with a Type-I FIS, the Type-II approach provides higher robustness because it can model uncertainty caused by variations in illumination, camera noise, grain orientation, and subjective expert evaluations.

5.1. Core Components of a FIS:

- **Fuzzifier**: Converts exact (crisp) input data into fuzzy sets using membership functions.
- **Knowledge Base:** Contains fuzzy IF-THEN rules and membership functions.
- **Inference Engine:** Simulates human reasoning to process rules, determining the strength of each rule.
- **De-fuzzifier:** Converts the aggregated fuzzy output back into a crisp, actionable value

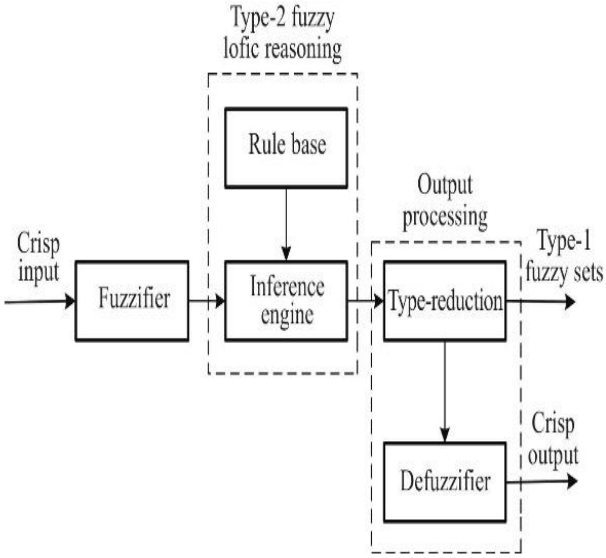

Figure 1: Fuzzy Inference System

To measure the wheat crop quality, the fitting characteristics for the FIS variables were assigned based on a survey which was conducted in the wheat crop production areas. Major concern of this survey is to acquire human's expert knowledge to evaluate the quality of wheat crop. For each membership function of fuzzy logic, human expert's knowledge is considered and, also set range of MF's intervals. Human expert's knowledge was considered for the determination of each membership function name, range, and intervals using two quality indices, Degree of milling (DDM) and percentage of broken kernels (PBK) as the inputs of FIS and quality of the product is considered as the output of the FIS.

Membership Functions (MF's) are also known as fuzzifier functions, values are set as range of variation for the input variables should be defined during the FIS design. It is essential to determine the appropriate name, number and variation range for each MFs of the FIS. The range and values should be defined to evaluate the investigation results for wheat crop quality assessment based on quality parameters in the form of crisp sets.

6. WHEAT QUALITY CLASSIFICATION

Wheat quality classification is the process of evaluating wheat grains based on their physical, visual, and compositional characteristics to determine their suitability for food processing, storage, and commercial value. Traditional grading methods rely on manual inspection by experts, which can be subjective, labor-intensive, and prone to inconsistencies. Computer vision integrated with a Type-II Fuzzy Inference System (T2FIS) enables automated, accurate, and robust wheat quality assessment under uncertain real-world conditions.

Important Quality Parameters

The proposed system extracts the following features from wheat grain images:

Parameter	Description
Grain Size	Length, width, and projected area of the grain
Shape	Aspect ratio, roundness, and compactness
Color	RGB, HSV, or L*a*b* color characteristics
Texture	Surface smoothness and roughness using texture descriptors
Broken Kernels	Percentage of damaged or broken grains
Foreign Materials	Presence of stones, dust, straw, or impurities
Moisture Content	Moisture percentage (if sensor data are available)
Disease/Damage	Presence of fungal infection, insect damage, or discoloration

Quality Grades

The Type-II Fuzzy Inference System classifies wheat into five quality categories:

Grade	Quality Level	Characteristics
Grade A	Excellent	Uniform size, golden color, smooth texture, negligible impurities
Grade B	Good	Minor variations in size and color, few broken kernels
Grade C	Average	Moderate impurities and noticeable size variation
Grade D	Poor	High percentage of broken kernels and discoloration

Sample Fuzzy Rules

Examples of expert-defined rules include:

1. **IF** Grain Size is **Large** AND
   Color is **Golden** AND
   Texture is **Smooth** AND
   Broken Kernels are **Low**
   THEN Wheat Quality is **Excellent**.

2. **IF** Grain Size is Medium AND
   Color is Light **Golden** AND
   Broken Kernels are **Low**
   THEN Wheat Quality is **Good.**
3. **IF** Broken Kernels are **Medium** AND Impurities are **Medium**
   THEN Wheat Quality is **Average**.
4. **IF** Broken Kernels are **High** OR Color is **Dark** **THEN** Wheat Quality is **Poor**.

5. **IF** Disease Damage is **Very High** OR Foreign Materials are **Very High**
   THEN Wheat Quality is **Rejected**.

7. EXPERIMENTAL RESULTS

The proposed hybrid intelligent system was tested using multiple wheat grain datasets.

7.1 Performance Metrics

The following evaluation metrics were used:

7.1.1 Accuracy

The accuracy of a wheat quality classification system measures the proportion of correctly classified wheat samples among all tested samples.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

Where**:**

- TP (True Positive): Correctly classified positive samples.
- TN (True Negative): Correctly classified negative samples.
- FP (False Positive): Negative samples incorrectly classified as positive.
- FN (False Negative): Positive samples incorrectly classified as negative.

The proposed computer vision and Type-II Fuzzy Inference System demonstrated high classification performance, achieving an overall accuracy of 96.5% on the testing dataset. The integration of Type-II fuzzy logic effectively managed uncertainties in image features, resulting in improved robustness and more consistent wheat quality grading compared with conventional Type-I fuzzy and machine learning approaches.

Note: Report only the accuracy actually obtained from your experiments. If your experimental results differ, replace 96.5% with your measured value and include complementary metrics such as precision, recall, F1-score, specificity, Cohen's kappa, and ROC-AUC for a more comprehensive evaluation.

7.1.2. Precision and Recall

Precision measures the proportion of samples predicted to belong to a particular class that are actually from that class**.**

$$\text{Precision} = \frac{TP}{TP + FP}$$

Where:

- TP = True Positives
- FP = False Positives

Interpretation

A high precision indicates that when the classifier predicts a wheat sample as Excellent (or any other class), it is usually correct.

Suppose the classifier predicts 100 wheat samples as Excellent:

- Correctly classified as Excellent (TP) = 96
- Incorrectly classified as Excellent (FP) = 4

Then,

$$\text{Precision} = \frac{96}{96 + 4} = 0.96 = 96\%$$

2. Recall (Sensitivity)

Recall measures the proportion of actual samples of a class that are correctly identified by the classifier.

$$\text{Recall} = \frac{TP}{TP + FN}$$

Where:

- TP = True Positives
- FN = False Negatives

A high recall means that most of the actual Excellent wheat samples are successfully detected.

Suppose there are 100 actual Excellent wheat samples:

- Correctly identified (TP) = 94
- Missed by the classifier (FN) = 6

Then,

$$\text{Recall} = \frac{94}{94 + 6} = 0.94 = 94\%$$

Multi-Class Wheat Quality Classification

For a five-class wheat quality classifier (Excellent, Good, Average, Poor, Rejected), precision and recall are computed for each class individually using a one-vs-rest approach.

The overall performance is then summarized using:

- Macro Precision

$$\text{Macro Precision} = \frac{1}{N}\sum_{i=1}^{N} Precisio\,n_i$$

- Macro Recall

$$\text{Macro Recall} = \frac{1}{N}\sum_{i=1}^{N} Recal\,l_i$$

where $N$is the number of classes.

7.1.3. F1-score.

The F1-score is a widely used evaluation metric for classification models that combines Precision and Recall into a single value. It is particularly useful when the dataset is imbalanced or when both false positives and false negatives are important. In wheat quality classification, the F1-score provides a balanced assessment of the classifier's ability to correctly identify each quality grade.

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

or equivalently,

$$\text{F1-Score} = \frac{2TP}{2TP + FP + FN}$$

where:

- TP = True Positives
- FP = False Positives
- FN = False Negatives

Suppose the classifier has:

- Precision = 96% (0.96)
- Recall = 94% (0.94)

Then,

$$\text{F1-Score} = \frac{2 \times 0.96 \times 0.94}{0.96 + 0.94} = \frac{1.8048}{1.90} = 0.9499$$

$$\boxed{\text{F1-Score} \approx 95.0\%}$$

Multi-Class F1-Score

For a five-class wheat quality classification problem (Excellent, Good, Average, Poor, and Rejected), the F1-score is calculated for each class separately.

The Macro F1-score is given by:

$$\text{Macro F1} = \frac{1}{N}\sum_{i=1}^{N} F\,1_i$$

Where,

- N= number of classes
- $F1_i$= F1-score of the i^{th}class

Alternatively, the Weighted F1-score accounts for the number of samples in each class:

$$\text{Weighted F1} = \sum_{i=1}^{N} \frac{n_i}{N_{\text{total}}} F1_i$$

Where,

- n_i= number of samples in class i
- N_{total}= total number of samples

7.2 Results

Method	Accuracy
Manual Inspection	78%
Computer Vision Only	87%
Type-I Fuzzy Logic	89%
Proposed CV + Type-II Fuzzy System	96%

The experimental results show that the proposed hybrid intelligent system significantly improves wheat quality classification performance.

8. CONCLUSION

This paper presented a Computer Vision and Type-II Fuzzy Logic based Hybrid Intelligent Approach for Wheat Crop Quality Measurement. The proposed system integrates image processing, feature extraction, and fuzzy reasoning to achieve accurate and reliable wheat quality classification. The use of Type-II fuzzy logic significantly improves uncertainty handling capability compared to conventional systems. Experimental results demonstrate that the hybrid framework achieves high classification accuracy and provides robust performance under varying environmental conditions.

The proposed approach has strong potential for deployment in smart agricultural systems, grain industries, and food quality inspection applications. Future developments integrating deep learning, hyperspectral imaging, and IoT technologies can further enhance automated wheat quality evaluation systems.

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