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ANN BASED AGE ESTIMATION OF PADDY GRAINS USING ADVANCED DIGITAL IMAGE TECHNIQUES

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Abstract- This paper explores the testing & implementation of advanced digital image processing techniques for age estimation of stored paddy grain over intervals of 0 to 16 months. The scheme is tested on the Pusa basmati variety of the paddy grain. The age estimation of paddy grains is crucial for optimal crop management and to ensure its quality and precise estimation of monetary value. The proposed age estimation technique involves a combination of Local Binary pattern (LBP) and Gabor features extraction technique which have been applied for first time to this domain of research. The LBP and Gabor features extracted from Paddy images of various age groups form a dataset to train an Artificial Neural Network (ANN) in MATLAB. Using these features, the ANN successfully classifies grain age, offering enhanced accuracy over conventional techniques. The results highlight the model's effectiveness and its potential for accurately determining the age of a particular variety of paddy, thereby catering the broader agricultural challenges in the domain of age estimation of crops. This underscores the promise of digital image processing and machine learning in refining age analysis of stored paddy, setting the stage for improved crop management strategies.

Index Terms- Age analysis, Digital image processing techniques, Gabor features, Local Binary Pattern (LBP) features.

1. INTRODUCTION

Paddy grains, initially golden yellow in color, undergo several physical and chemical alterations with the passage of time during storage, manifesting into the color change of its outer husk. These changes, from altered starch content to fat oxidation, are linked with changes in the grain's physical attributes such as shape, color, and texture. The transformations due to ageing affect multiple stages in the life of the grains, from harvest and storage to cooking and selling. Moreover, the age of the grains affecting their quality, are also influenced by the grain type or variety and their storage medium. Freshly harvested rice, for example, tends to be sticky when cooked, while rice stored for nearly half a year produces drier & fluffier results. The better cooking properties of aged rice makes them more preferable to consumers, fetching higher market prices & profits for older grains. So, accurate age determination of paddy grains is crucial for many, from consumers to farmers.

One significant sign of ageing in the paddy grains is the change in the color of their husk. While traditionally, experts determined the age by visually inspecting the grain colors; this method seems to be subjective and isn't efficient for large batches of paddy crops. An intelligent, automated & accurate technique for determining the age of grains would therefore help everyone in the supply chain of paddy in order to quickly ensure the right age of rice and consequently its quality.

While modern imaging has brought innovations to farming, not much work has been done in determining the age of paddy grains using this technique. Though a very few image processing techniques have been earlier reported for age estimation of rice using color indices, these researches

were more oriented to their quality analysis rather than accurate and precise age estimation. Moreover, the approach adopted in these works were limited to a few specific paddy varieties aged within vary narrow time range.
The paper adopts a novel technique for age estimation of the Pusa Basmati variety of paddy grains. The method involves power image features extraction technique such as *local binary pattern* (LBP) and *Gabor features*. The efficiency of the proposed method has been tested and found to be sufficiently accurate for age estimation of paddy grains.
The paper is structured as follows:
Introduction in section 1 is followed by a literature survey of existing age estimation techniques presented in section 2, section 3 contains an overview of methodology followed and the materials required, and finally the results & discussion are presented in section 4, and conclusions of the study are incorporated in the section 5.

2. Literature Survey

In order to delve deeper into the latest researches in the intelligent grain age estimation for food crops, an in-depth literature review was carried out. Not much literature was available on the image-based age estimation of paddy grains. Most of the research works carried out in this domain were restricted to the quality analysis of paddy grains. A few essential insights drawn from the literature review are presented below:
Choe *et.al.* (2013) introduced a color vision method to determine Malaysian paddy grain maturity by observing the hue and floret weight. The work followed the approach of converting the RGB image data of paddy into their HSV image. Then they calculated hue values of the HSV image at different points. The calculated hue values were used to train ANN using back propagation algorithm. The trained ANN was able to classify the different paddy images with an accuracy of 96.66%. Hence, the back propagation ANN model emerged as an effective instrument for paddy grain age classification, achieving very high accuracy with 13 color attributes [1]. The study however, could assess the paddy age for a very short duration when the paddy crop was in the field. It did not study the ageing of the grains after harvesting and during storage period.
Srikaeo *et.al.* (2013) performed chemical age analysis of rice grains ageing between 0-6 month duration. They probed into the color variations in chemical reagents for rice grains of different ages, using a spectrophotometer. The three-color spaces namely L*, a* and b* were identified for the rice images. L*represented the image lightness on 1–100-point scale and a*b* represented the colors of human vision red, green, blue and yellow for the rice images. A difference in the values of above parameters amongst the images was used to distinguish the young paddy grains from the aged ones [2].
Azman *et. al.* (2014) suggested employing color indices as an effective means to gauge the moisture level and maturity phases of rice. This was achieved by utilizing color attributes from thermal and RGB images. The five pivotal color indices red, green, blue, thermal red, and thermal index were identified for the rice images. These color indices were used to develop linear estimation models. It was observed that the model involving red index, gave the estimation of maturity and moisture contents with success rates of 99.5% and 99.4% respectively [3].
Further extending their research, Azman et al. (2015) unveiled a fresh approach for paddy maturity estimation through seven color indices sourced from RGB color spectrum. The indices were red, green, blue, green-blue difference, green-red difference, green to blue ratio, and green to red ratio. The study indicated a significant correlation between these indices and paddy's maturity levels [4].
Jinorose *et. al.* (2016) introduced a rice quality evaluation method using the HSI color models [5] Xiaoli *et al.* (2018) implemented a chemometrics technique combined with visible/near-infrared reflectance spectroscopy to differentiate paddy seeds based on storage durations, registering a notable average accuracy of 97.5%.

This study was limited to only four rice types with a restricted sample size. It was also remarked that paddy husk color transformation was swift during the first 12 months of natural storage and slowed down subsequently afterwards. These findings highlight the essence of the study thereby underscoring the demand for a more holistic and accurate grain aging evaluation.[6]
Most of the studies listed above were aimed at paddy quality detection during their different phases of maturity. Moreover, they did not consider the effect of storage medium in the age detection. The approach followed in this work aims to cater the short comings associated with these previous studies.
The application of image processing in the agricultural sphere is broadening, offering intricate and nuanced analyses. From crop assessment at varying growth phases to yield forecasts, disease detection, and pest management, digital image processing plays a pivotal role. Specifically, for paddy grains, image analysis can be invaluable in determining grain age, assisting in forecasting harvest timelines, yield predictions, and overall crop stewardship.

3. Materials and methods

The techniques used and methodology followed for preparing the data from the obtained paddy images have been presented in this section.

3.1 Techniques used

The technique involves extraction of local binary pattern (*LBP*) and Gabor features from the obtained images of the paddy grains. These two features present in the images have been briefly discussed in subsequent sections.

3.1.1 Local Binary Pattern

LBP is a proven technique for texture analysis of images which was introduced in mid-1990s. The technique involves converting the images into pixels first and then selecting a square matrix portion from the obtained pixel values preferably in the form of a 3x3 matrix in as given in equation (1). The central element k_{center} and other elements, k_1-k_8 are used to calculate the LBP 1 values in equation (2). Finally, the pixel values are converted into another 3x3 matrix LBP 2 represented in equation (3) containing binary values on the basis of conditions represented in equation (4) (*Dulaimi et al. 2020*). Then a histogram of all LBP values in the image is compiled to form a feature vector representing the image.

$$B = \begin{bmatrix} k_8 & k_1 & k_2 \\ k_7 & k_{center} & k_3 \\ k_6 & k_5 & k_4 \end{bmatrix} \tag{1}$$

$$LBP1 = \begin{bmatrix} k_8 - k_{(center)} & k_1 - k_{(center)} & k_2 - k_{(center)} \\ k_7 - k_{(center)} & k_{(center)} & k_3 - k_{(center)} \\ k_6 - k_{(center)} & k_5 - k_{(center)} & k_4 - k_{(center)} \end{bmatrix} \tag{2}$$

$$LBP2 = \begin{bmatrix} s(k_8 - k_{(center)}) & s(k_1 - k_{(center)}) & s(k_2 - k_{(center)}) \\ s(k_7 - k_{(center)}) & k_{(center)} & s(k_3 - k_{(center)}) \\ s(k_6 - k_{(center)}) & s(k_5 - k_{(center)}) & s(k_4 - k_{(center)}) \end{bmatrix} \tag{3}$$

$$s(x) = \begin{Bmatrix} 1 & if\ x \geq 0 \\ 0 & if\ x < 0 \end{Bmatrix} \tag{4}$$

Finally, 8-bit binary pattern representing the LBP values for the image sample are encoded as in equation (5).

$$LBP = \sum_{a=0}^{8} s(k_a - k_{center}) 2^p \tag{5}$$

Where p represents the sum of binary values calculated for neighborhood pixels w.r.t the central pixel.

3.1.2 Gabor Features

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Gabor filters, inspired by the work of Dennis Gabor, are pivotal tools in texture analysis, focusing on capturing specific frequency content within localized regions of an image. By detecting edges, textures, and extracting key features, they delve into the spatial frequency, orientation, and phase of image structures, making them valuable in pattern recognition and computer vision.

For age analysis of paddy grains, Gabor features can distinguish subtle texture shifts due to maturation, encompassing variations in color, size, shape, and surface roughness. By processing images of paddy grains through Gabor filters, these features can be extracted and subsequently employed to gauge the grain's age. Integrating these extracted features with machine learning models can revolutionize age prediction in paddy grains (*Bera et al. 2018*).

Gabor Function for an image is given by $f(x, y)$ in equation (6)

$$f(x, y) = \iint I(\alpha, \beta) g(x - \alpha, y - \beta) d\alpha d\beta \tag{6}$$

Where g(x,y) is represented by equation (7)

$$g_{(\lambda,\theta,\varphi\sigma,\gamma)}(x, y) = \exp\left(-\frac{x^2+\gamma^2 y^2}{2\sigma^2}\right)\cos\left(\frac{2\pi x}{\gamma} + \varphi\right) \tag{7}$$

where,

$$x = acos\theta + bsin\theta$$
$$y = -\operatorname{acos}\theta + bsin\theta$$

λ- wavelength of Gabor function cosine factor
θ- Orientation of Gabor function
ϕ- Phase off-set of Gabor function
σ- Standard deviation of Gaussian factor
γ- Ellipticity of the Gaussian factor

3.1.3 ANN model

Artificial Neural Networks (ANN) are adaptive systems inspired by the way the human brain processes information. As ANN can mimic the human brain action; they can be trained using different algorithms to perform the sophisticated tasks such as differentiation amongst a data-set of patterns representing images. ANN is usually composed of interconnected nodes (or "neurons") in a layered structure similar to human brain. Usually, ANN is composed of three layers as depicted in figure 1. The first layer called the input layer is where the data for training is usually fed into the ANN. The second layer called hidden layer is responsible for processing the data and extracting features for differentiation between the two data types. The features are extracted by generally adjusting the weights and bias values of neurons in the hidden layer. ANN with multiple hidden layers form the Deep neural networks (DNN). Finally, the output of final prediction and classification are obtained at the output layer (*Sazli M. H. 2006*).

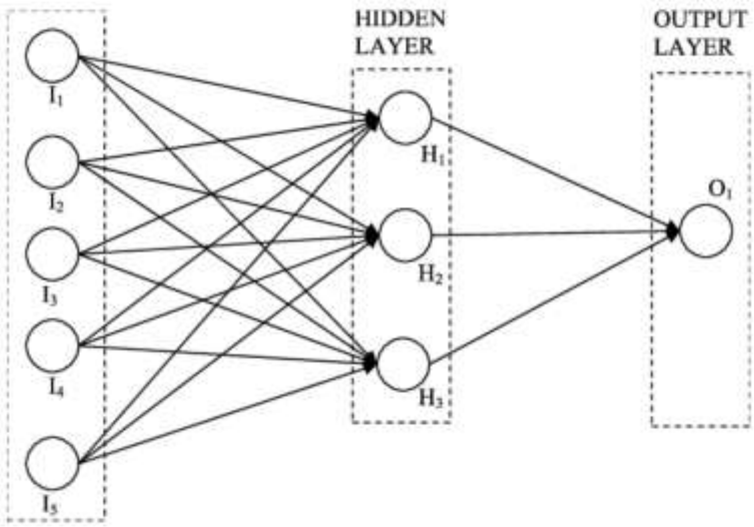

Fig- 1 ANN structure.

3.2 Methodology

The methodology adopted for obtaining the paddy images and their classification using ANN is included in this section.

3.2.1 Image acquisition and pre-processing

In order to obtain the paddy images a dedicated apparatus was developed to facilitate the controlled and standard capture of paddy images. The inner views of designed apparatus for image acquisition are in figures 2(a) and 2 (b) however, figure 3 shows its image with paddy sample placed inside. A mobile phone equipped with a 48-megapixel camera was used to capture 3210 RGB colored images in JPG format.

This step involves capturing images of paddy grains at various stages of their lifecycle. The images were captured under controlled conditions to ensure consistency and minimize external factors that could influence the image characteristics. The quantity and quality of the images taken are essential as they would directly impact the accuracy of the machine learning model in the subsequent phase. The apparatus and their specifications used for obtaining the paddy image data are presented in table 1.

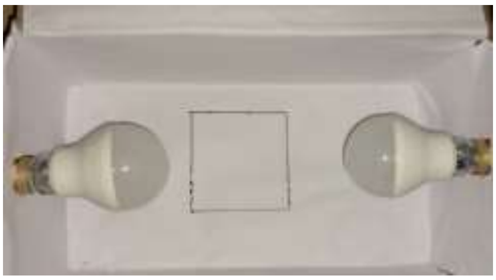

Fig-2(a) Inner view of image acquisition apparatus. Fig-2(b) Front view of image acquisition apparatus.

Fig-3 Image acquisition apparatus with paddy sample.

Table 1: Features of the image acquisition apparatus.

Apparatus	Features	Description
Card-board box	Dimensions	Length – 29 cm Breadth – 15 cm Height – 11 cm
	Material used	Cardboard
	Interior coating	Lined with plain white paper from uniform and neutral background
	Box cover	Removable for protection from external disturbances. Helps prevent ambient light interference.
Mobile Phone camera	HD resolution camera	50 MP, 1920x1020 display resolution
Light arrangement	Two opposite placed LED bulbs	9 watt, 370 lumens bulb with crystal white light

3.3 ANN based age classification

For age estimation, the Pusa Basmati paddy grains are categorized into one of eight ageing periods using machine learning, relying on Gabor and LBP features from processed images. Gabor filters extract texture characteristics from these images, indicative of grain maturation. After feature extraction, a machine learning model is trained with these features to predict the age of the grains. Once trained on a subset of the data, the model's accuracy is tested on a separate subset. The final result is a model capable of estimating the age of paddy grains from their image features, serving as a valuable tool for agricultural age analysis. The complete flow chart of the processes involved in age estimation process are depicted in figure 4.

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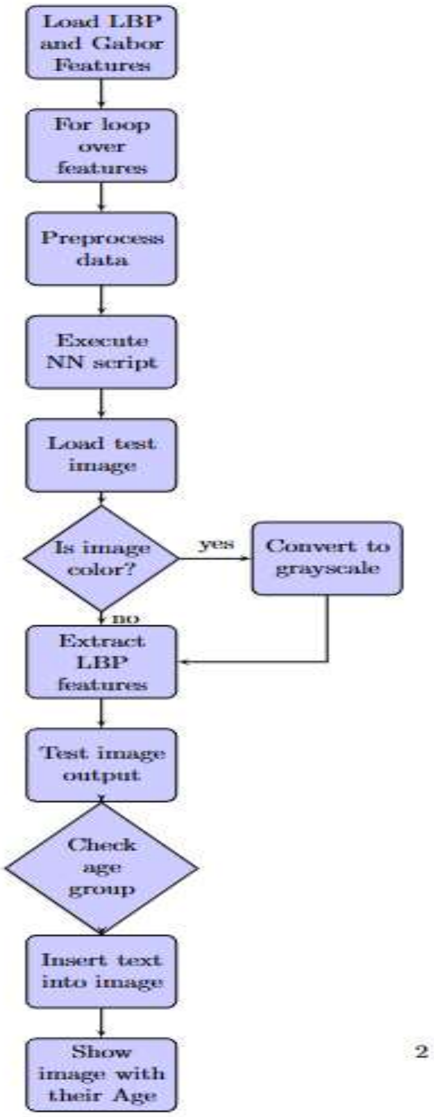

Fig- 4 Flow chart of the age estimation process

First, images were pre-processed which includes normalization, noise reduction, and contrast enhancement. Gabor features were then extracted by applying Gabor filters, which are linear filters used for texture analysis and feature extraction. They analyze the image's frequency content in localized regions, capturing the texture characteristics of paddy grains indicative of their age. Subsequently, Local Binary Pattern (LBP) features are extracted, summarizing the local spatial structure of the image. In MATLAB, the Gabor and extracted LBP feature functions retrieve these features. Finally, the Gabor and LBP feature vectors train ANN model to classify the paddy grains by their ageing periods.

The figure 5 showcases the effective training process of the ANN using the paddy grain dataset. The architecture of the network is designed such that it accepts 59 distinct inputs and provides 8 distinct outputs, each corresponding to a specific age interval of the paddy grains.

The 59 inputs represent the LBP and Gabor features extracted from the paddy grain images. These features capture crucial texture and spatial frequency information related to the aging process of the grains. This substantial feature set provides a comprehensive understanding of the grains, thereby enabling precise age determination.

The ANN is trained to map these 59 inputs to one of the 8 output age groups: 0-2 months, 2-4 months, 4-6 months, 6-8 months, 8-10 months, 10-12 months, 12-14 months and14-16 months. The

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training process involves adjusting the network's internal parameters i.e., weights and biases to minimize the error between the predicted and actual age group.

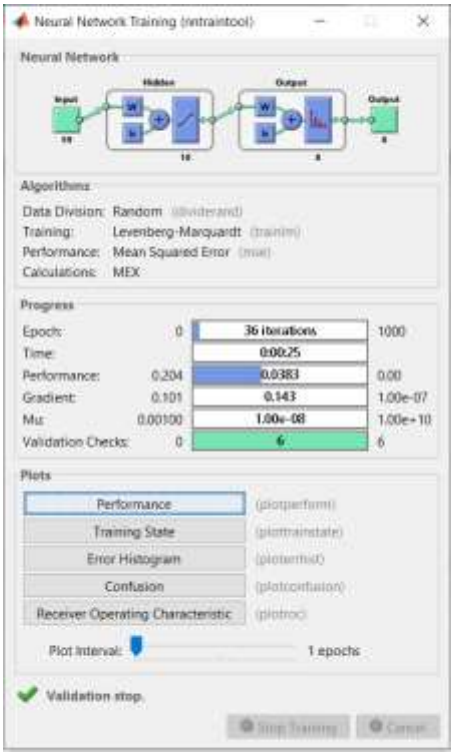

Fig-5 ANN training parameters.

4. Results and discussion

The results, after the implementation of the MATLAB code, reaffirmed the initial findings of the high accuracy of the ANN model in identifying and classifying the age of paddy grains.
The MATLAB code executed an ANN model trained with LBP and Gabor features. The trained model was then used to classify the age of the paddy grains into eight distinct age intervals: 0-2 months, 2-4 months, 4-6 months, 6-8 months, 8-10 months, 10-12 months, 12-14 months, 14-16 months. The model, when tested with an external paddy grain image, effectively computed the feature set of the image, passed through the trained ANN and delivered an output that categorized the grain into one of the eight age groups. This output was subsequently overlaid on the original image for visual validation, providing a user-friendly way of showcasing the results.
Figure 6 shows the ANN model's performance over 36 epochs during training, validation, and testing phases. The model's error reduces significantly with each epoch, optimizing at the 30th epoch with a validation error of 0.083439. This indicates its best predictive accuracy for the validation set. While the error values converge up to the 30th epoch, they diverge after, hinting at overfitting. The model's rapid learning and generalization across 36 epochs emphasize its suitability for real-world applications. Figure 7 provides a set of four confusion matrices corresponding to the training, validation, testing and overall performance of the ANN model. A confusion matrix is a valuable tool for evaluating the performance of a classification model, as it quantifies the model's predictions against the actual values, thereby offering insights into the accuracy, precision, recall and specific areas of misclassification.

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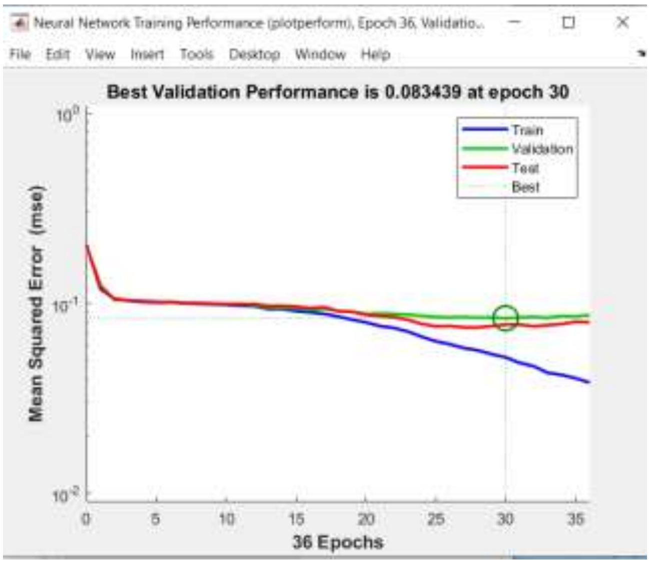

Fig- 6 Performance Evolution of the neural network.

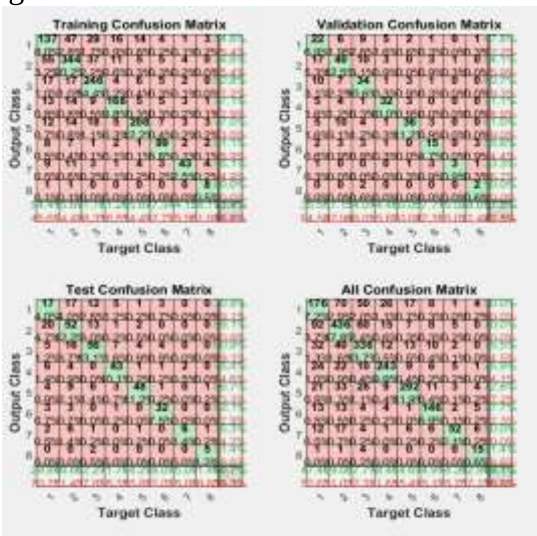

Fig- 7 Set of Four Confusion Matrices.

These confusion matrices are defined as:

(a) Training confusion matrix: This matrix depicts the performance of the model on the training data set. It shows how well the model has learned the patterns and relationships from the data it was trained on. The diagonal elements represent instances where the predicted age group matches the actual age group, which is the ideal scenario. Off-diagonal elements indicate instances where misclassifications occurred.

(b) Validation confusion matrix: This matrix shows the performance of the model on the validation set, which is unseen data that the model did not train on. It is used to tune the model parameters and avoid overfitting. The performance on this matrix is crucial because it provides a fair indication of how well the model generalizes to new data.

(c) Test Confusion Matrix: This matrix provides insights into the model's performance on the test data set which is another set of unseen data. The accuracy derived from this matrix is usually taken as the final performance metric of the model as it indicates how the model will perform in real-world scenarios.

(d) Overall Confusion Matrix: This matrix aggregates the results from the training, validation and test sets to give an overall performance measure of the model. It provides a complete overview of the model's performance across all the data.

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Figure 8 displays an error histogram for ANN model during training, validation, and testing. The histogram has 20 bins, each representing a range of error values. The training error histogram shows 10,000 instances at the -0.05 bin, indicating minimal training errors. The validation error histogram has 12,000 instances in the same bin, suggesting the model generalizes well. The test error histogram shows 15,000 instances at the -0.05 bin, highlighting the model's strong performance and reliability on test data. There are 12,000 instances in the -0.05 bin, indicating that the model was also able to generalize well to new, unseen data.

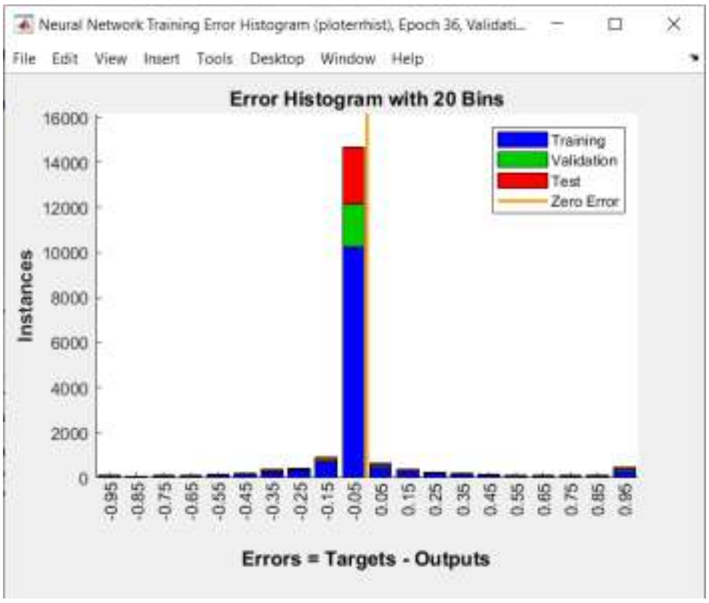

Fig- 8 Error histogram

Figure 9 depicts the ANN model's ability to predict paddy grain age using texture and spatial frequency information from images. The model, trained on age intervals ranging from 0-16 months, extracts features using LBP and Gabor methods. Results highlight the model's accuracy in classifying grain age, emphasizing its reliability. The MATLAB execution validates the model's robustness. Overlaying predictions on original images aids users like farmers in making informed decisions, enhancing the model's real-world applicability. This approach paves the way for automated crop management and smarter agriculture, with potential expansion to other grain types in future research.

Fig- 9 Paddy grain (Pusa Basmati) estimated age of different images.

Conclusions

The trained ANN model has proven to be highly efficient and accurate in estimating the age of paddy grains. By using Local Binary Pattern (LBP) and Gabor features, the model effectively analyzes texture and spatial frequency information of grain images and accurately categorizes them into distinct age intervals.

The performance evaluation of the model, across 36 epochs, confirmed its ability to learn and generalize patterns effectively, reaching an optimum at the 30th epoch with an error of 0.083439. However, the tendency of the model to overfit beyond the 30th epoch suggests that future implementations might benefit from early stopping or other regularization techniques to prevent overfitting.

Confusion matrices and error histograms provided a detailed insight into the model's performance during training, validation and testing phases. They highlighted its ability to make accurate predictions with minimal errors, demonstrating the robustness of the ANN model in practical applications.

The ANN model not only successfully classified paddy grains into their respective age groups but also overlaid this classification onto the original grain image. This visual representation enhances the usability of the model and enables users to make quicker, data-driven decisions, advancing the field of smart agriculture.

References

[1] Choe L. H., Wan Ismail, W. I., Kairunniza-Bejo, S., Putih, A. and Shamshiri, R. (2014), “Color vision to determine paddy maturity”, International Journal of Agricultural and Biological Engineering, Vol.7, 2014, pp55-63.

[2] Srikaeo, K. and Panya, U. (2013) , “Efficiencies of chemical techniques for rice grain freshness analysis”, Rice Science, Vol.20, 2013, pp292-297.

[3] Azman N., Khairunniza-Bejo, S., Ismail, W. I. and Wayayok, A. (2014), Estimating Maturity of Paddy Using RGB Color Space. J. Adv. Agric. Technol., Vol.1, 2014, pp123-128.

[4] Azman N., Bejo, S. K., Wan Ismail, W. I. and Wayayok, A. (2015) , “Development of Fresh Harvested Paddy Quality Determination Model Using Color Indices” , Australian Journal of Basic and Applied Sciences, Vol.9, 2015, pp50-56.

[5] Jinorose M., Somkiat, P. and Somchart, S. (2016), “Development of a computer vision system and novel evaluation criteria to characterize color and appearance of rice”, Drying Technology, Vol.28, 2016, pp1118-1124.

[6] Xiaoli Li., He, Y. and Wu, C. (2018), “Non-destructive discrimination of paddy seeds of different storage age based on Vis/NIR spectroscopy”, Journal of Stored Products Research, Vol.441, 2018, pp264-268.

[7] Dulaimi H. K., Mostafa, S., Mustapha, A., & Nasrudin, M. F. (2020), “Review of local binary pattern operators in image feature extraction”, Indonesian Journal of Electrical Engineering and Computer Science, Vol.19, 2020, pp23-31.

[8] Bera S., Sharma M., & Singh, B. (2018), “Feature extraction and analysis using Gabor filter and higher order statistics for the JPEG steganography”, International Journal of Applied Engineering Research, Vol.13, 2018, pp2945-2954.

[9] Sazli M. H. (2006), “A brief review of feed-forward neural networks”, Communications Faculty of Sciences University of Ankara Series A2-A3 Physical Sciences and Engineering, Vol.50, 2006, pp11-17.