



Research Article

Prediction of Potato Volume by Neural Network Regression Model

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Article Information

Received: 18 May 2024
Revised: 09 September 2024
Published: 25 September 2024

Abstract

Potatoes are essential for meeting the world's dietary requirements due to their high concentration of carbohydrates, vitamins, and minerals. Potato production is plentiful worldwide, but postharvest processing losses have reduced potato quality. Potatoes can be graded manually, which is time-consuming and labor-intensive. In this study, a neural network regression model was developed to predict the volume of potatoes using 2D images, which can be used as a parameter for grading potatoes automatically. The image processing method was used to extract features like the major axis, minor axis, and roundness of 400 potato samples, and each potato's volume was thoroughly measured using the water displacement method, and a dataset was generated. These attributes were used to create the neural network regression model and predict the volume. The results revealed that the mean squared error (MSE) was 83.93, the root mean squared error (RMSE) was 9.16, and R^2 was approximately 0.882. The potatoes were categorized into three groups: small, medium, and large, based on their size. The utilized model demonstrated an overall accuracy rate of 91.4%. Specifically, it achieved 90% and 85% accuracy for small-sized and medium-sized potatoes, respectively, whereas the model displayed a decrease in accuracy from 60% to 70% for large-sized potatoes. To summarize, the suggested neural network regression model provided an efficient approach to volume prediction using 2D images to improve the grading process of agricultural products.

Keywords: Grading, Potato, Volume prediction, 2D Image processing, ANN, Regression model

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1. Introduction

Agriculture has been the primary income source in rural Bangladesh, contributing significantly to GDP growth. According to the Bangladesh Bureau of Statistics, in the fiscal year 2021–22, agriculture accounted for 11.50% of the GDP. Potatoes (*Solanum tuberosum*) are a key agricultural product in Bangladesh, and it is the seventh-largest potato producer globally [1]. In Bangladesh, the annual production rate of potatoes is approximately 11.829 million metric tons [2]. Globally, potatoes are widely consumed, with over 100 countries including them in their diets [3].

Despite abundant production, significant losses occur. Due to postharvest diseases, 8.83% loss occurs and 13.78% due to physical abnormalities. The highest abnormalities were observed in green potatoes at 6.20%, followed by cut potatoes at 4.27% and pitted potatoes at 2.10% [4]. Postharvest loss ranges from 20% to 25% and is a significant issue in potato production [5]. Grading potatoes by size, shape, and quality reduces postharvest losses, ensuring only the best market reach. Potatoes can be graded manually or using advanced techniques. Manual grading of potatoes is complex and tedious, categorizing them into groups based on attributes such as shape, volume, color, and irregularities [6]. It requires a lot of labor and can result in discrepancies [7]. Manual grading methods involve manual sorting by size, color, and shape (ovate or oblong), hindering economic growth and agricultural development

Cite This Article

Rahman, F., Das, J., Mamun, M.R.A., Haque, M.M., Upoma, S.M., Rahman, A., and Ashik-E-Rabbani, M. 2024. Prediction of potato volume by neural network regression model. *Journal of Agricultural Machinery and Bioresources Engineering*, 8(2):40-52. <https://doi.org/10.61361/jambe.v8i2.124>

as the process is time-consuming [8]. Besides, this is prone to inconsistency and inaccuracies in judgment [9]. So, to meet the demand for food and reduce poverty, agricultural research and technological advances are needed to boost agricultural output [10].

Grading potatoes based on volume using machine vision techniques is an innovative approach that can replace and reduce manual grading processes in industries like agriculture, food processing, and manufacturing. In the last few years, machine vision has become increasingly beneficial in every field of the food industry, especially for checking the quality of the fruit and sorting it by shape [11]. Recent work has shown a tomato grading machine vision system that utilized image processing techniques and machine learning algorithms. The suggested approach achieved an average accuracy of 0.9515 in detecting calyx and stalk scars in both defective and healthy tomatoes [12]. Certain authors have shown machine vision systems that enhance accuracy without direct contact, minimizing potato damage, but they necessitate costly cameras, image processing software and algorithms [13]-[14]. Image processing involves fundamental operations to enhance image data by reducing distortions and further improving significant features for analysis tasks [15]. This technology has extensive applications in agriculture, with identification and classification posing significant challenges for computer vision to achieve human-like recognition capabilities [16]. Researchers are developing systems to automatically classify fruits based on cultivar, and quality using various image processing approaches and machine learning classifiers like support vector machines, K-nearest neighbour classifiers, and artificial neural networks.

Artificial neural networks (ANNs) are a collection of technologies commonly associated with artificial intelligence. They aim to replicate the neural processes of the human brain [17]. An ANN model may exhibit a high level of accuracy [18]. As a result, they can be effectively employed for both data fitting and prediction tasks [19]. A study was conducted on hyperspectral fruit and vegetable classification using convolutional neural networks and proposed a simple method for categorizing hyperspectral photos using cutting-edge convolutional neural networks (CNN) pre-trained on RGB image data [20]. Besides, a system was developed that can classify mangoes in terms of color, volume, size, shape, and fruit density [21].

Beside these techniques, neural network regression has resolved numerous technical issues [22]. A regression neural network is a one-pass learning algorithm with a highly parallel structure. Effectiveness has been shown in several areas of agricultural remote sensing, particularly in categorizing crop types and calculating crop areas. They utilized two types of Artificial Neural Networks, namely a Generalized Regression Neural Network (GRNN) and a Radial Basis Function Neural Network (RBFNN), to predict the production of potato crops that were planted using distinct methods [23]. A research showed [24] that leaf diseases seriously affect the crop's growth and yield quality; this study aims to develop a recognition system that detects the presence of disease in the mango leaf using an image processing technique. The developed system effectively detects and classifies the disease with an accuracy of 68.89%, which is a low result of the need for more training images.

Unlike typical grading techniques that rely on weight or surface faults, this study takes a unique way to predict potato volume using neural network regression that improves grading accuracy and provides a more complete output assessment by focusing on volume, which is strongly related to quality and market value. It also takes a cost-effective strategy by using more accessible and inexpensive imaging technologies, which lowers the overall cost of the grading process while maintaining accuracy. This alternate method compares efficiency and performance in addition to a new take on predictive modeling. Other research uses difficult and expensive 3D imaging for grading, but this research uses 2D image to estimate potato volume which streamlines the imaging procedure.

In this research, an image processing technique and a neural network regression model were used to predict potato volume for grading. Key features such as the major axis, minor axis, and roundness were extracted from 2D images of the potatoes. This method integrates advanced data processing and machine learning to provide a reliable and efficient tool for assessing both volume and grading purpose, enhancing the accuracy of predictions and supporting better decision-making in grading management and inventory control. The specific objectives of this research are to create a unique dataset for predicting potato volume and to formulate a regression model for potato volume prediction.

2. Materials and Methods

This section describes how a neural network regression model predicted potato volume from 2D images. Features extracted from the 2D picture via image processing were utilized to fit the prediction model. A photo studio was developed, and the major axis, minor axis, and volume were calculated manually. Different measures were employed to evaluate the model.

2.1 Sample collection

The Diamond variety of potato (*Solanum tuberosum*) used for this research was obtained from a local market. A sample of 400 potatoes was randomly picked from market in different batches and categories to provide a representative sample.

2.2 Image acquisition and image pre-processing

A setup was developed and 2D images of potatoes were taken by mobile phone camera in order to accomplish the desired objective. The image format was jpg. A customized photography box was developed to capture photos, with four corner lights, black cloth inside, and white paper at the bottom for a neutral background to avoid shadows and highlight potato features. Made of plywood, the box measurements were 22" × 14" with a height of 7", covering an area of 308 in². Figure 1 illustrates the box used for capturing potato images.

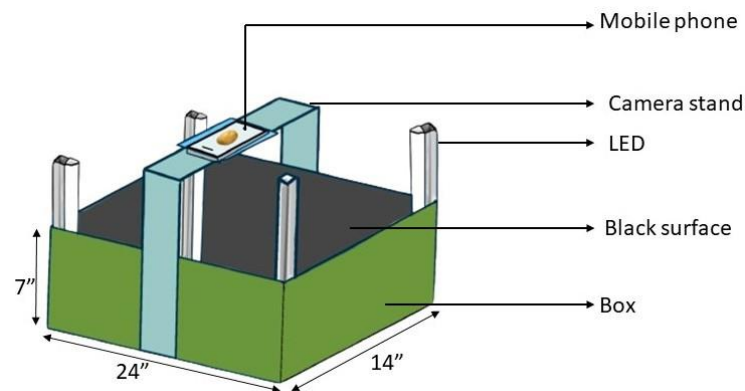


Figure 1. Custom-designed box for capturing potato images.

A Samsung Galaxy A54 50 Megapixel camera was fixed at an 8" height, capturing images in raw JPG format from a consistent perspective. Continuous lighting was provided through an electrical connection, ensuring high-quality images ideal for extensive study. The camera focused on the central point of each potato.

2.3 Manual data collection

The potatoes were sequentially numbered, and accurate measurements were taken for the major axis, minor axis, and volume. The potato's major and minor axes were manually measured with digital slide callipers. The object's volume was determined using Archimedes' water displacement technique. A cleaned and dried beaker filled with water, with the original water level (V_1) scrupulously recorded (Figure 2 a). The potato was gently put in the water-filled beaker, ensuring it was entirely immersed and not touching the rims or the bottom. The change observed in water level (V_2) was precisely recorded (Figure 2 b).

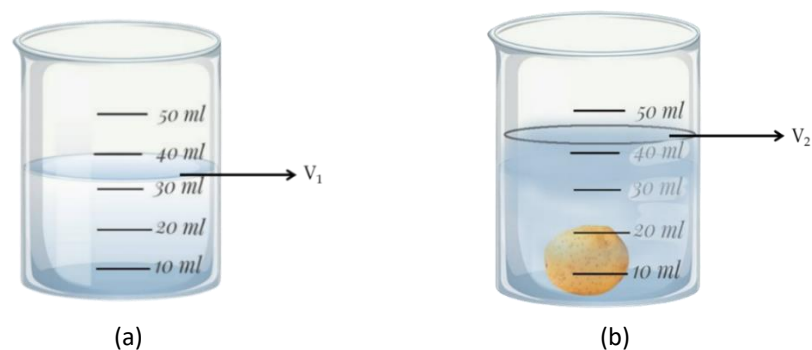


Figure 2. Beaker for volume measurement (a) without potato (b) with potato

The formula for volume calculation,

$$V = V_2 - V_1 \tag{1}$$

Here, Initial volume of water = V_1 and Final volume of water after potato was placed= V_2 .

Each potato was carefully placed to ensure accurate measurements, which were then compared to values derived from 2D photographs using image processing.

2.4 Morphological feature analysis of potato

Through image processing, the roundness, major axis, and minor axis of potato images were measured [25].

Major axis: It is the longest straight line that can be traced through the center of the potato, from one end to the other, passing through its widest points. Where x_1, x_2, y_1, y_2 indicate the co-ordinates of a potatoes X and Y axes.

$$\text{Major axis length} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{2}$$

Minor axis: The minor axis describes the ellipsoidal potato's shortest dimension or axis. Put another way, it's the shortest straight line that can be drawn through the potato's narrowest points, across its center, and perpendicular to its major axis.

$$\text{Minor axis length} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{3}$$

Roundness: Roundness is a numerical measurement of how closely the form of an object resembles a mathematical circle or sphere. First eccentricity value was measured for measure roundness value. The roundness value shown in equation (5).

Eccentricity: Eccentricity is a geometric term that describes the measure of how elongated or flattened a shape is compared to its ideal or circular form[25]. The eccentricity value shown in equation (4).

$$\text{Eccentricity} = \sqrt{1 - \frac{(\text{SemiMajor})^2}{(\text{Semi minor})^2}} \tag{4}$$

By following the equation (4) roundness was find.

$$\text{Roundness} = 1 - \text{eccentricity} \tag{5}$$

2.5 Image feature extraction

Digital images are often represented in image processing as arrays of numerical values, with each value indicating the colour or intensity of a pixel in the image. This is done to facilitate the processing of data. The flow diagram in Figure 3 represents the process of extracting features from potato images.

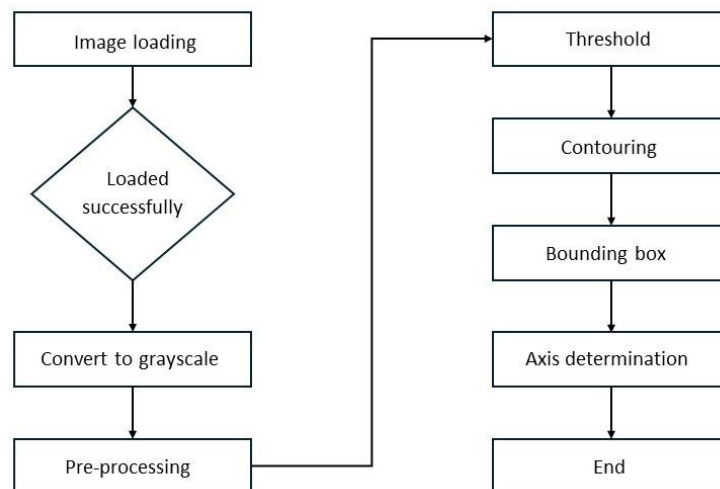


Figure 3. Flow diagram of axes determination of potato using open cv.

Images were loaded and converted to grayscale. The conversion process of a colour image to a grayscale image was explained using the following equation [26].

$$\text{GRAY image} = W_r * R + W_g * G + W_b * B \quad (6)$$

Here, W_r is the coefficient (fixed weight) of red color and the value is 0.299; W_g is the coefficient (fixed weight) of the green color and the value is 0.587; W_b is the coefficient (fixed weight) of blue colour and the value is 0.114.

The threshold image was obtained on the grayscale image to produce a binary image using the following equation (7), where the potato was visible against the background [27].

$$g(x, y) = \begin{cases} 1, & \text{for } f(x, y) > T \\ 0, & \text{for } f(x, y) \leq T \end{cases} \quad (7)$$

Where,

$g(x, y)$ is defined as the threshold image; $f(x, y)$ is the source image; and T is the threshold value.

The binary picture was processed to find the contours corresponding to the boundaries of the things represented. An ellipse was then drawn around this contour, making it easier to determine the lengths of the major and minor axes. Finally, the potato's roundness was established by computing the ratio of minor axis length to major axis length and eccentricity.

2.6 Model prediction

Several software platforms and tools were used to create a model to predict the volume of potatoes. These tools provide various functions, including model creation, training, and deployment. Google COLAB was selected because it allows users to create and run Python machine-learning algorithms in a Jupiter notebook. It provides free CPU, GPU, and TPU (Tensor Processing Unit) resources, making it a great choice for machine learning and deep learning projects. The libraries used included NumPy, Pandas, Scikit-learn, Keras, TensorFlow, OpenCV, and Matplotlib.

2.6.1 Neural network regression

Neural networks, a type of machine learning algorithm, are influenced by the structure and functioning of the human brain. The structure is made up of layers of networked nodes or neurons. The major axis, minor axis, and roundness were used as input for the model. Two hidden layers, each consisting of 64 neurons, were used with a RELU activation Function. For the output, one layer with one neuron was used with a linear activation function, which was suitable for the regression task and efficient optimizer used for training the model. General equation for regression neural network is shown below [28].

$$E [Y | X] = \frac{\int_{-\infty}^{\infty} y f(x, y) dy}{\int_{-\infty}^{\infty} f(x, y) dy} \quad (8)$$

Here, Y = output predicted by neural network regression model

X = input vector ($x_1, x_2, x_3 \dots$)

The following figure (4) illustrates the architecture of the neural network model.

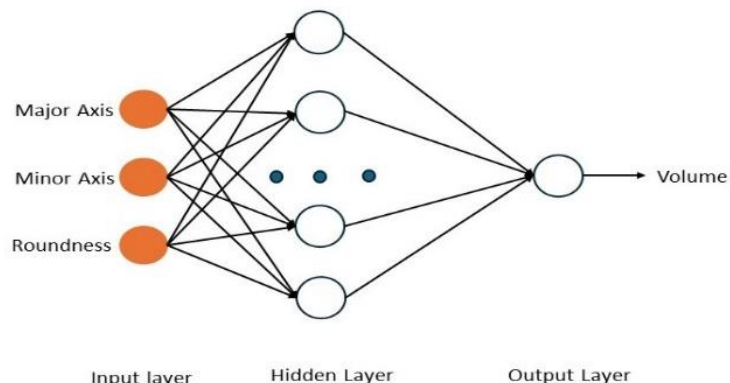


Figure 4. Neural network regression architecture.

2.6.2 Volume prediction process

The neural network regression model predicted potato volume using image-processed features: major axis, minor axis, and roundness. Data were pre-processed and standardized for model training, which involved three input neurons, hidden layers, and an output neuron for volume prediction. The model's fit and accuracy were evaluated using Mean Squared Error (MSE). Training used 60% of the dataset, with 40% for verification. The trained network assessed potato volume based on the features after testing its accuracy on a separate set. Figure 5 shows basic flow for neural network regression model.

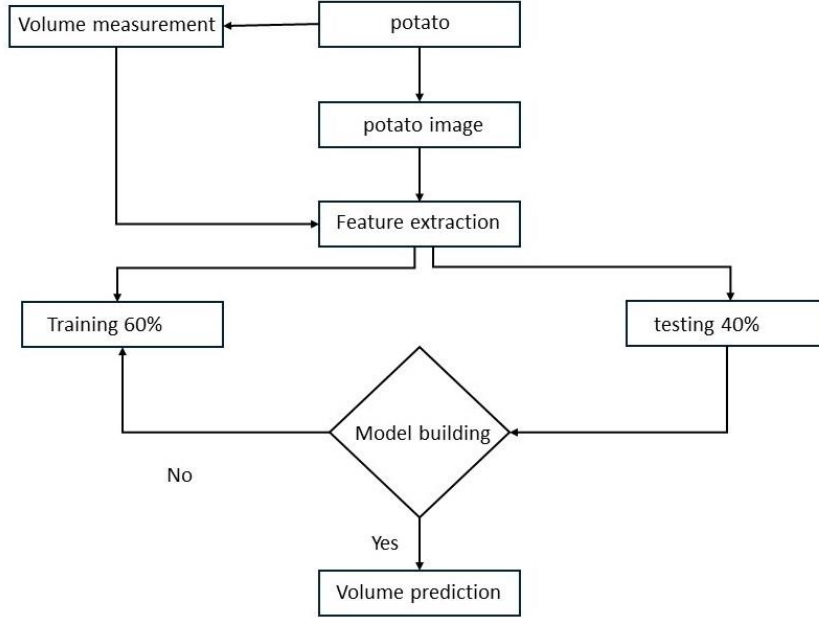


Figure 5. Basic flow for building neural network regression model.

2.7 Performance evaluation of the model

Error calculation is crucial for evaluating the model's performance on image processing system. The formula for calculating error metrics is given below [29]

Mean squared error (MSE): Understanding how well the model fits to the data needs the average squared difference between the actual values and the anticipated value evaluated by the mean squared error (MSE).

$$MSE = \frac{1}{m} \sum_{i=1}^m (y_i - y'_i)^2 \quad (9)$$

Root mean squared error (RMSE): Root Mean Square Error is the square root of the average of the squared differences between expected and actual values. It was used to assess how incorrect a model is when anticipating quantitative data.

$$RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^m (y_i - y'_i)^2} \quad (10)$$

Mean absolute error: The Mean Absolute Error was used to assess the efficacy of regression models without taking into account the direction of the error. Calculate the average absolute difference between planned and actual values.

$$MAE = \frac{1}{m} \sum_{i=1}^m |y_i - y'_i| \quad (11)$$

R² Metrics: R-squared, or the coefficient of determination, used to indicate the proportion of variance in the dependent variable that is predictable from the independent variables. An R² score close to 1 indicates a good fit.

$$R^2 = 1 - \frac{\sum_{i=1}^m (x_i - y_i)^2}{\sum_{i=1}^m (y' - y_i)^2} \quad (12)$$

Here, m is the number of data point, y_i is the actual value, y'_i is the predicted value.

2.8 Accuracy analysis of the model

The Mean Absolute Percentage Error (MAPE) expresses the accuracy as a percentage, it provides a clear interpretable measure of error in percentage terms. The formula for calculating accuracy [29]

$$\text{MAPE} = \frac{1}{m} \sum_{i=1}^m \left| \frac{y_2 - y_1}{y_1} \right| \quad (13)$$

Here, n is number of observations, y_1 is actual volume, y_2 is predicted volume

If $\text{MAPE} < 10\%$ that means the model forecasting accurately

$10\% \leq \text{MAPE} < 20\%$: Good forecasting.

$20\% \leq \text{MAPE} < 50\%$: Reasonable forecasting.

$\text{MAPE} \geq 50\%$: Inaccurate forecasting.

3. Results and Discussion

3.1 Morphological feature extraction on COLAB

The image was imported on COLAB and converted to grayscale to simplify and ensure robustness against colour and lighting variation. The image was thresholded for conversion into a binary image, and the potato was isolated from the background. After the contouring process was done to identify the precise boundaries of the potato, the major and minor axes and roundness were measured. Figure 6 shows the grayscale, threshold, and contouring image.

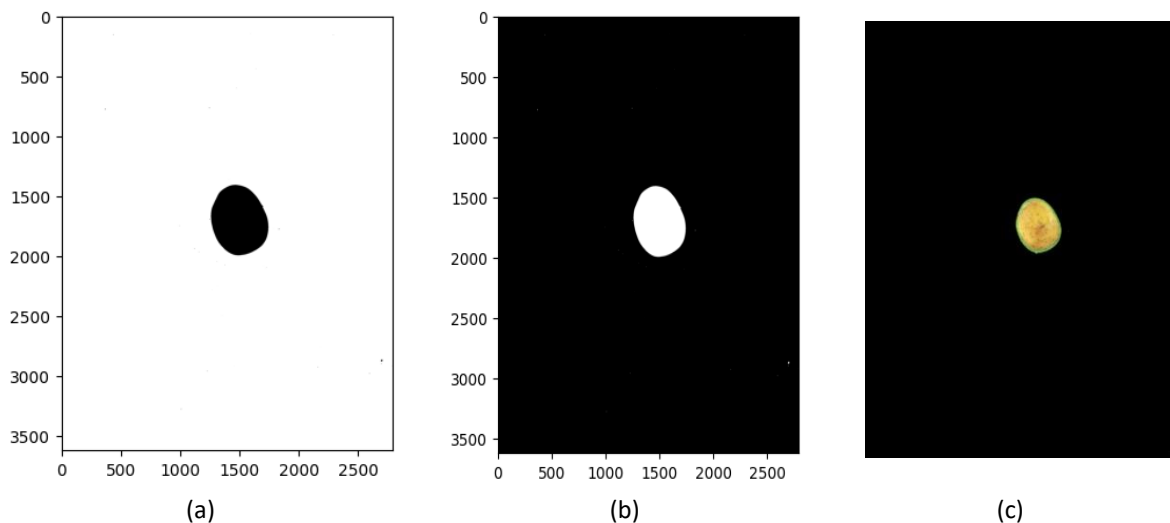


Figure 6. (a) Grayscale image, (b) Threshold image, and (c) Contouring image.

3.2 Verification of image processed features

Manually calculated major and minor axes were compared to image processing values. Figures 7 and 8 represent this comparison. Discrepancies happened due to camera angle, lens distortion, or manual measurement errors. Though different image-processed data had about 96% accuracy, making them relevant.

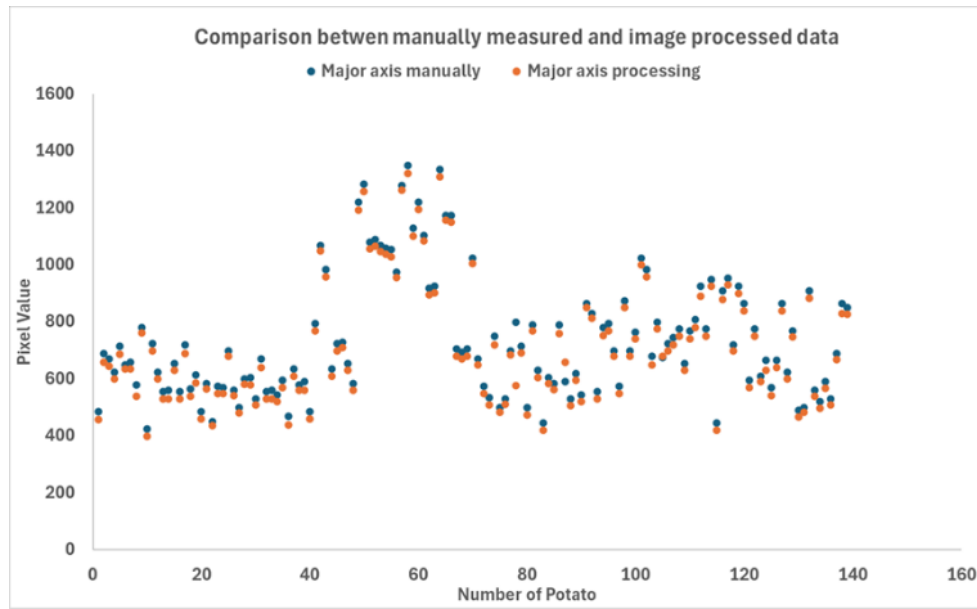


Figure 7. Comparison of manual and image processed data for major axis.

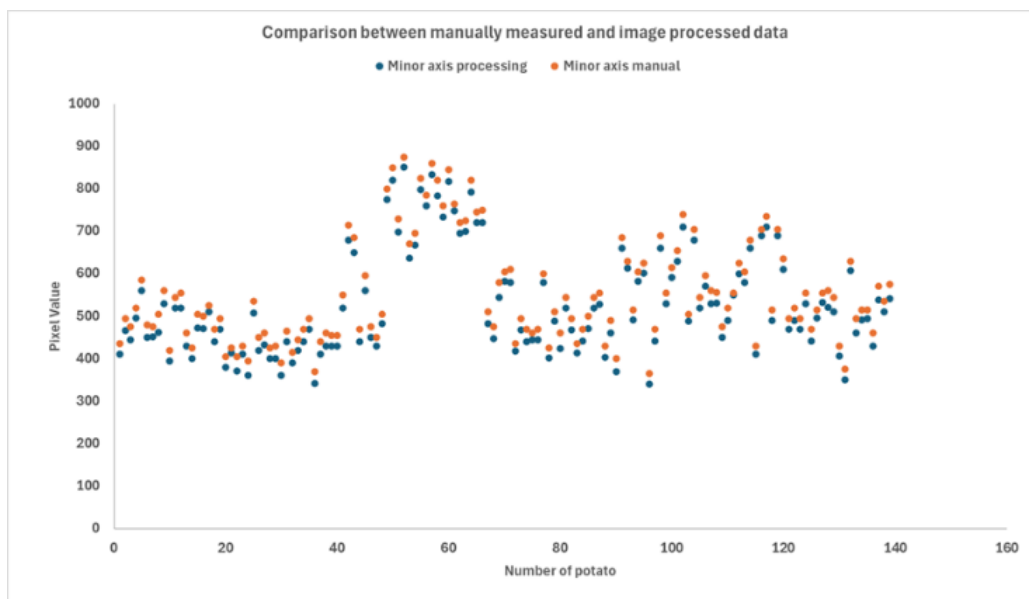


Figure 8. Comparison of manual and image processed data for minor axis.

3.3 Model error and accuracy analysis

Model performance analysis and visualization were necessary to establish how well the model functioned. Several graphs were used to illustrate the model's performance.

3.3.1 Training and validation loss over epochs

In Figure 9, the training and validation loss reduced with each epoch, indicating that the model learned well and was not overfitting to the training data, which was a desired result since it suggested that the model was likely to perform well on unknown data. Because the model is first attempting to identify patterns in the training data, the training loss line in figure declined quicker than the validation loss line.

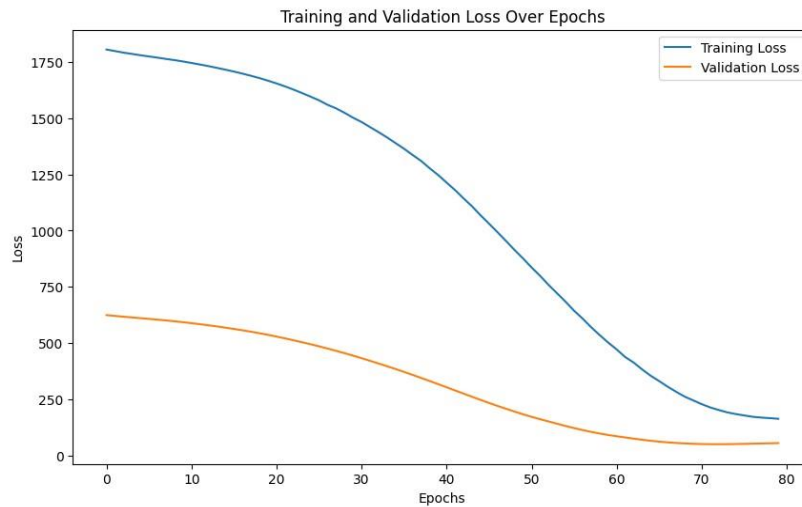


Figure 9. Training and validation loss plot.

3.3.2 Training and validation MAE over epochs

Training and validation loss show how successfully the model learns and generalizes to new data. Figure 10 shows training and validation MAE over epoch.

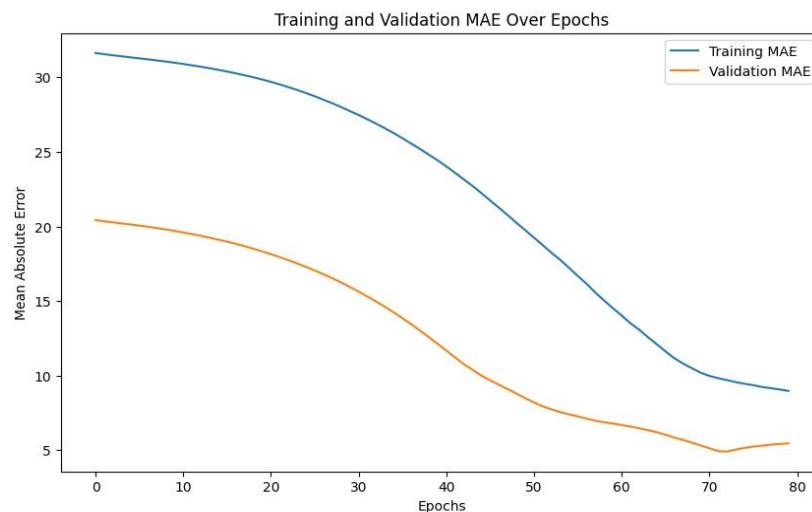


Figure 10. Training and validation MAE over epoch.

Here, the training MAE and validation MAE were decreased over time. Both losses decreased simultaneously, indicating that the model's capabilities and training procedure was match the data. Means that the model complexity was acceptable for the situation and was neither overfitting nor underfitting.

3.3.3 Predicted volume vs actual volume

Figure 11 shows the observed volumes vs predicted volumes for a certain model. Each blue dot represents a single data point. The red line represents the ideal circumstance in which the projected volumes match the actual ones exactly. In the figure, the blue dots were tightly spaced around the red line and sometimes fitted to the red line, indicating that the model generally made accurate predictions. The graph demonstrated that the model was performing well.

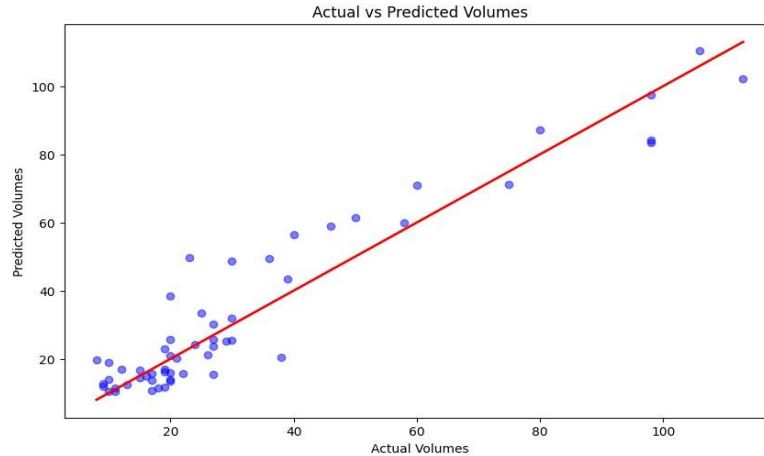


Figure 11. Predicted volume vs actual volume.

3.3.4 Residuals vs predicted volumes

Figure 12 shows the relation between residuals and predicted volumes. Residual plots help to analyze regression model fit. The residuals (the difference between the observed and estimated values) were compared to the estimated values or another relevant variable. A random residual distribution around the horizontal line at $y=0$ indicates a successful model. The model improved if the residuals showed a clear pattern or trend. The residual graph for this regression model showed no trend. The residuals were distributed randomly, with some deviating 20 units higher and some lower than $y = 0$. Because the model frequently provided accurate estimations. This result is normally favorable for little potatoes, whereas accuracy decreases for large potatoes. Overall, the pattern of residuals suggested that the model worked very well for small-size potatoes, but it required improvement to predict large-size potatoes.

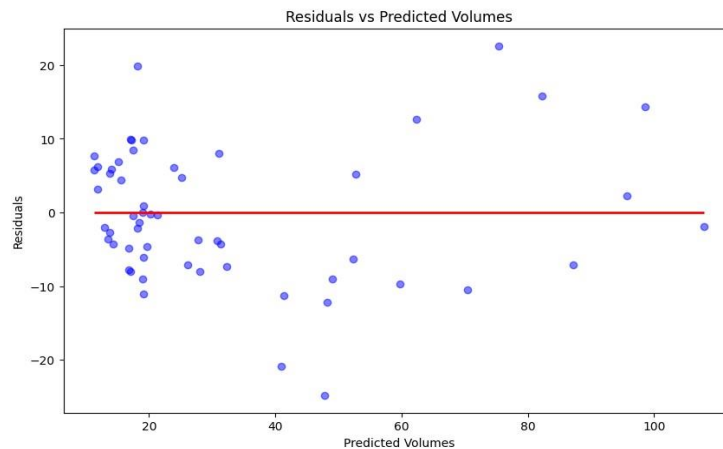


Figure 12. Residuals vs predicted volumes.

3.4 Error analysis of neural network regression model

Mean squared error (MSE): It means that, on average, the squared differences between the actual values and the predicted values in this model are 83.7 which is higher, and a higher MSE suggests that the predictions deviate more from the actual values which indicates that the model is fit satisfactorily [30].

The root mean squared error (RMSE): The RMSE is 9.16 which demonstrates that the model has a good level of accuracy in predicting the volume of potatoes from 2D images. The RMSE is increasingly larger than the MAE [30].

The mean absolute error (MAE): The MAE provides a measure of the average magnitude of errors in a set of predictions, without considering their direction (whether the errors are positive or negative). The MAE is 7.37 for this model which means the model has a robust predictive capability.

R-squared (R²) metric: R² typically ranges between 0 and 1[31]. Here the R² is around 0.882, which explains 88.2% of the variation in potato volumes, leaving 11.8% unexplained. This might be attributable to unaccounted-for causes or intrinsic variability. The error indicates that the method of combining image processing for feature extraction with neural network regression was an effective strategy for predicting potato volumes.

3.5 Model accuracy

Accuracy was determined using the Mean Absolute Percentage Error (MAPE). The MAPE for little potatoes was 7%, indicating that the model predicted the appropriate amount of small potatoes; for medium-sized potatoes, the MAPE rose to 12%. The MAPE for large potatoes was 27%, indicating that the provided model could not accurately forecast enormous potatoes. The morphologies of the potatoes may explain differences in accuracy for these categories; a small or medium roundness score of approximately 1 suggested that the potato was almost spherical and uniform in all dimensions. Conversely, large potatoes had a more diverse form depending on how they were observed, and the roundness value increased to 0.4-0.5, resulting in an incorrectly calculated volume. Because of the potatoes' odd form, the algorithm had a harder difficulty while accurately predicting their number.

4. Conclusions

This research focused on developing a general regression neural network model for predicting the volume of potatoes using 2D images for grading. Predicting potato volume is complex due to shape variability. Uneven, non-axisymmetric geometries impair accuracy, especially for large potatoes. A regression neural network model for volume prediction was developed in this investigation, achieving an accuracy of 91.4%, the mean absolute error was 7.37%, the R² error was 88.2%, mean absolute percent error was 7%. So, the neural network regression model's accuracy, adaptability, and efficiency make it a current option for potato volume prediction that meets agricultural expectations for precision and mechanization. The algorithm, trained on a dataset of 400 potatoes, risks underfitting due to inadequate data. A larger dataset would help the model identify patterns, enhancing accuracy. Including more attributes also improves prediction accuracy. Various recommendations can be pursued to overcome the limitations of using 2D images for volume prediction, such as increasing the dataset size, exploring more image features, employing better image processing techniques, and considering alternative neural network models. Developing a real-time system for estimating potato volume could also enhance accuracy.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used “Conceptualization, Muhammad Ashik-E-Rabbani; methodology, Fawzia Rahman, Md. Mashurul Haque, Sidratul Muntaha Upoma and Joy Das; software, Fawzia Rahman; validation, Fawzia Rahman, Joy Das and Anisur Rahman; formal analysis, Anisur Rahman; investigation, Muhammad Ashik-E-Rabbani and Md. Rasel Al Mamun; resources, Muhammad Ashik-E-Rabbani; data curation, Md. Rasel Al Mamun; writing—original draft preparation, Fawzia Rahman and Joy Das; writing—review and editing, Md. Rasel Al Mamun; visualization, Fawzia Rahman and Joy Das; supervision, Muhammad Ashik-E-Rabbani; project administration, Muhammad Ashik-E-Rabbani; funding acquisition, Muhammad Ashik-E-Rabbani. All authors have read and agreed to the published version of the manuscript.”

Acknowledgments: This research was made possible by the support of the Department of Farm Power and Machinery, Bangladesh Agricultural University, and the Ministry of Science and Technology, Government of the People's Republic of Bangladesh.

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