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Implementation Of Convolutional Neural Network (CNN) Based On Mobile Application For Rice Quality Determination

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***Abstract* – The purpose of this study is to design and build CNN deep learning modeling for mobile web browser applications on the quality classification of rice types and analyze the performance of the model in real time. The method applied is an experimental method that utilizes machine learning technology, namely teachable machine by using the results of videos converted into images as datasets. This image dataset is classified based on its shape, color and background, which is used as a reference for the training dataset. Once the CNN training model is formed, it is then set up in a web editor p5.js then an interface is created to connect to a server such as Google Cloud using FastAPI, which can be accessed using a mobile application or web browser such as Chrome. In the mobile application, create an interface to connect with the camera system and datasets on the cloud server. The results of the study were obtained that the CNN-based modeling developed was quite accurate in classifying the quality of rice types. In the model test with file data input and camera input, the model accuracy confidence level reached 96% to 99%, with an average percentage of 97.33%. The results of the accuracy confidence level in web browser testing reached 98% to 100%, with an average percentage of 99%.**

Keywords: CNN, rice, dataset, training, web browser, accurate

I. INTRODUCTION

In this modern era, information technology continues to experience rapid advancement, creating opportunities to apply innovations in various areas of life. One important aspect that can be improved is the determination of rice quality, which is an integral part of the agriculture and food sectors. Technology plays an important role in processing, storing, and disseminating information [1]. Information technology can be used to support the decision-making process in monitoring rice and rice prices [2], [3]. In addition, the application of technology in agricultural operations, such as the development of advanced information systems, is essential to improve competitiveness and support national food security [4], [5]. In the context of rice quality, the development of integrated rice quality control applications with feature-based development methods has been proposed to answer the challenges in rice quality control [6]. In addition, digital image analysis has been explored for rice quality classification, demonstrating the potential of the technology to contribute to assessing rice quality [7].

Rice quality is a crucial factor in ensuring food security and community welfare. By combining the capabilities of the Convolutional Neural Network (CNN) and the mobile application, it can create an effective and efficient solution for assessing the quality of rice. The integration of CNN and mobile apps offers an effective and efficient solution for assessing rice quality. Deep learning algorithms in CNN, which are popular in image processing, have been successfully applied in various domains including visual image quality assessment [8]. The use of CNN in assessing rice quality shows its potential to evaluate rice quality [9]. In addition, CNNs have been widely used in computer vision, demonstrating their application in image-based assessments, including rice quality evaluations [10], [11].

Rice quality determination traditionally involves manual methods that tend to be time-consuming, error-prone, and require special expertise. Thus, the application of CNN technology offers a faster, more accurate, and up-to-date approach to rice quality assessment [12], [13]. CNN has been successfully applied in various fields demonstrating its potential for accurate and efficient analysis in various domains [14]. The integration of CNNs with mobile applications including web browsers has been highlighted as a measurable and far-reaching intervention, demonstrating the potential to use CNN-based systems providing an effective solution for rice quality assessment [15]. The development of an efficient desktop application-based rice quality evaluation system, utilizing computers and machine learning, further supports the potential for technological advancement in rice quality assessment [16].

The application of CNNs in deep learning, demonstrates its ability to automatically identify specific patterns and characteristics related to rice quality. CNNs have demonstrated high performance, effectiveness and good accuracy in a wide range of applications, in identifying and classifying rice [17]. The use of CNNs is quite flexible in handling quality evaluation in the context of agricultural applications [18], [19], [20]. In addition, the development of a CNN-based framework for the identification of rice grain varieties and the classification of rice varieties is considered to be aqueous and efficient in assessing rice quality [21], [22], [23]. The app was chosen because of its ability to extract features from visual data. The quality of rice can be reflected in visual aspects such as the color, shape, and integrity of the rice grains. By designing a suitable CNN model, it will be able to recognize and evaluate the quality of rice with high precision, and its performance shows the potential to assess quality with little additional computing cost [24]. The application of CNN proved to be effective, with a high degree of accuracy, demonstrating its potential to recognize visual patterns related to rice quality attributes [25], [26], [27]. In addition, CNNs have been successfully applied in various fields, such as object detection and color texture classification, demonstrating their versatility for precise visual recognition tasks [28], [29], [30].

The use of mobile applications in the form of web browsers as a platform for CNN implementation brings significant benefits in terms of accessibility and speed. By taking advantage of the sophistication of mobile devices, users can easily access this rice quality determination tool anywhere and anytime. This facilitates farmers, traders, and consumers to conduct assessments instantly, improving the efficiency and accuracy of results [31], [32]. Embedding CNNs with web browsers allows smart applications to become a reality. This is because the CNN architecture with efficient memory can facilitate detection and identification based on the development of mobile applications such as web browsers that show its practicality and effectiveness in mobile application platforms [33] because it is able to classify various assessment potentials in real-time [34]. This is what makes CNN a platform that is able to assess the quality of rice efficiently and accurately [35].

Based on this, the development and implementation of a CNN-based teachable machine, which can be integrated into mobile applications such as web browsers for rice quality assessment, is expected to provide tools that can improve efficiency in determining rice quality, reduce reliance on manual methods, and support overall food security. The integration of CNN's teachable machine into the mobile app offers significant benefits in terms of accessibility and speed, allowing users to access rice quality assessment tools anywhere and anytime for instant evaluation, thereby improving the efficiency and accuracy of results [36], [37], [38], [39], [40], [41], [42]. CNN has been successfully utilized in various real-time assessment potentials using a CNN-based mobile platform [43], [39], [40]. Thus, it is hoped that the results of this implementation will make a positive contribution to the development of a more sophisticated and reliable rice quality assessment system and can pave the way for the development of similar technologies in agriculture and other food sectors. This implementation is also expected to provide innovative solutions, helping to increase productivity and quality in the agriculture and food sector as a whole, including supporting halal issues..

II. METHOD

This research uses an experimental method that utilizes machine learning technology by using a lot of image data, in the form of a type of rice which is then used as a dataset (data set). These data are also first classified by shape, color and background. For example, the data for brightly colored rice will be classified separately with slightly black rice data. The images that become the data are pictures and videos of rice taken using digital cameras. Furthermore, all of these images are used as a reference for the dataset to be trained. The more data is entered, the more optimal the learning system will be, which allows the test results and validation to be more accurate and precise.

The training process, first a learning model is made. With this CNN method, the number of layers and networks used cannot be predicted because the learning process itself will depend on the type of image data to be trained. The type of data in question is the shape, color, lighting and background of the image of the object taken with the camera. This condition will make the training process will take place repeatedly, with different models. Until finally, a model was obtained from CNN learning that would be used.

After the CNN-based teachable machine model is formed as a training model, then the file in the form of a TensorFlow.js (TF.js) is downloaded and arranged in a web editor p5.js then an interface is created to connect to a server such as Google Cloud using FastAPI, which will later be accessible using a mobile application or Web Server such as Crome. For the mobile application, an interface will also be created to connect with the camera system and data base on the cloud server. The modeling mindset for web applications using tensorflow is shown in the following image:

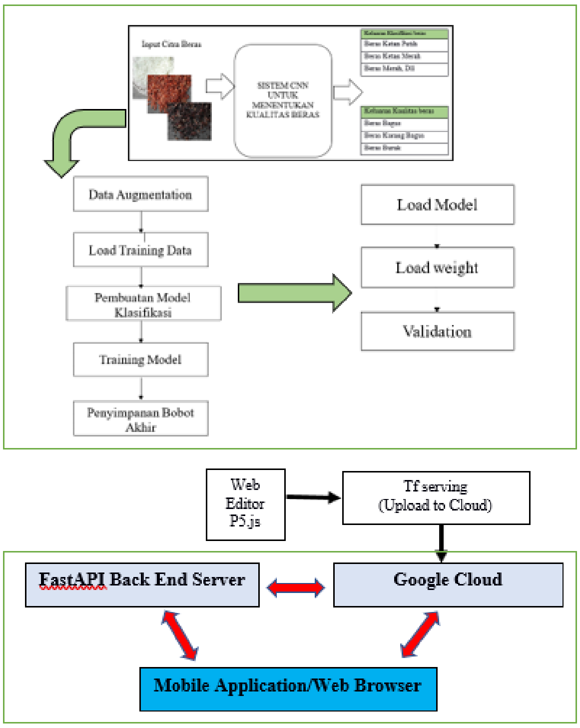

Figure 1 Block diagram of designing a rice classifier based on a mobile application

The block diagram above shows the rice classification process using a CNN-based teachable machine for a mobile web browser application. The rice image dataset used as input will provide many kinds of samples in determining the features, shape and color of the rice to be classified. This study used 9 (nine) types of rice, namely Head Rice, Groin Rice, Brown Rice, Santana Rice, Sidrap Rice, Black Glutinous Rice, Red Glutinous Rice, White Glutinous Rice, Ordinary White Glutinous Rice. Each type of rice is placed on a different color background. There are 10 (ten) color backgrounds used, namely Light Blue, Dark Blue, Light Brown, Dark Brown, Green, Black, Light Yellow, Pink, Dark Red, and Orange. Each type of rice is recorded using a camera in the form of an 8 to 10-second video that is taken 10 times for each type of rice with a different color background using a minimum resolution of 1080p. Then the entire rice video was converted into images that were used as data sets. The conversion results from the image dataset amounted to 5992 images as the primary dataset.

Rice datasets will be classified and also augmented data such as image brightening, image rotation and image folding which allow data to be more varied to be used as input datasets in conducting the training process on CNN-based teachable machines. In the teachable machine, the number of (1) epochs is determined, namely one full cycle of the entire dataset during the model training process. Each image in the dataset will be processed once per epoch, (2) batch size is the number of images processed at once before the model updates its weight, and (3) learning rate which is the input text of the model as the tolerance of the model in carrying out the training process. The settings made are Epochs of 50, Batch Size of 128, and Learning Rate of 0.001. The image dataset will be trained and a classification model training process will be carried out until it is obtained how accurate and how many percent of the data is likely to be recognized when the model is finished and used to recognize the type of rice given.

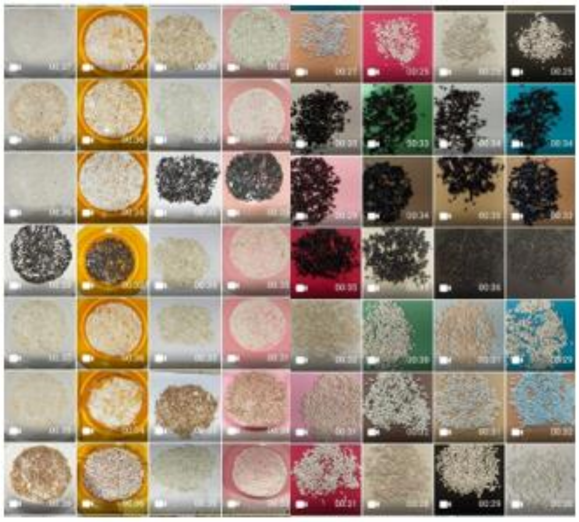

Figure 2. Making a video of rice samples with various backgrounds

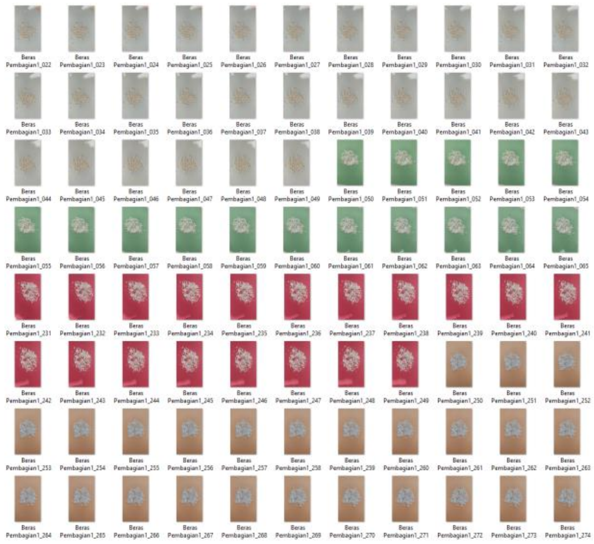

Figure 3. Image set (JPG) data snippets fed into Teachable Machine

Furthermore, these models will be extracted and exported into existing formats such as json models, json metadata, weight bin models, tensorflow models, and or hard. The model used for the website application is the .json model. This .json model is included in the editor website p5.js. The results of the files obtained are then uploaded to Google Cloud as one of the cloud-storage used for this training model. Then the model that has been made can be used to classify the type of rice according to the input given.

In the classification process, using a camera on the hardware of the computer or laptop that accesses the link that has been generated.

III. RESULTS AND DISCUSSION

a. Results Classification of Rice Types

The classification of rice objects that have been trained and the classification model has been saved in the form of a .js file, which previously used the Epochs setting of 50, Batch Size of 128 and Learning rate of 0.001. The model can be called and can be used to predict the level of confidence in the image of the new type of rice based on 9 classes, namely head rice, black glutinous rice, red glutinous rice, white glutinous rice, brown rice, Menir rice, santana rice, Sidrap rice, ordinary white glutinous rice.

Once the entire display is set up, then create the source code for the p5.js website editor. The following is an image of the source code snippet in the p5.js website editor.

```
<div>Teachable Machine Image Model - p5.js and ml5.js</div>
<script src="https://cdn.jsdelivr.net/npm/p5@latest/lib/p5.min.js"></script>
<script src="https://cdn.jsdelivr.net/npm/p5@latest/lib/addons/p5.dom.min.js"></script>
<script src="https://cdn.jsdelivr.net/npm/ml5@latest/dist/ml5.min.js"></script>
<script type="text/javascript">
 // Classifier Variable
 let classifier;
 // Model URL
 let imageModelURL = 'https://teachablemachine.withgoogle.com/models/OEA9VM0jf/';

 // Video
 let video;
 let flippedVideo;
 // To store the classification
 let label = "";

 // Load the model first
 function preload() {
  classifier = ml5.imageClassifier(imageModelURL + 'model.json');
 }

 function setup() {
  createCanvas(320, 260);
  // Create the video
  video = createCapture(VIDEO);
  video.size(320, 240);
  video.hide();

  flippedVideo = ml5.flipImage(video);
  // Start classifying
  classifyVideo();
```

Figure 4 Source code snippets for website editors p5.js

After the source code is completed, then a preview is carried out to ensure that the source code works properly. When the source code is in the form of coding, then the model results derived from the TensorFlow.js results are uploaded to Google Cloud. The following is an image of the source code snippet uploaded on google cloud.

```
<div>Teachable Machine Image Model</div>
<button type="button" onclick="init()">Start</button>
<div id="webcam-container"></div>
<div id="label-container"></div>
<script src="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs@latest/dist/tf.min.js"></script>
<script src="https://cdn.jsdelivr.net/npm/@teachablemachine/image@latest/dist/teachablemachine-
image.min.js"></script>
<script type="text/javascript">
  // More API functions here:
  // https://github.com/googlecreativelab/teachablemachine-community/tree/master/libraries/image

  // the link to your model provided by Teachable Machine export panel
  const URL = "https://teachablemachine.withgoogle.com/models/OEA9VM0jf/";

  let model, webcam, labelContainer, maxPredictions;

  // Load the image model and setup the webcam
  async function init() {
    const modelURL = URL + "model.json";
    const metadataURL = URL + "metadata.json";

    // load the model and metadata
    // Refer to tmImage.loadFromFiles() in the API to support files from a file picker
    // or files from your local hard drive
    // Note: the pose library adds "tmImage" object to your window (window.tmImage)
    model = await tmImage.load(modelURL, metadataURL);
    maxPredictions = model.getTotalClasses();

    // Convenience function to setup a webcam
    const flip = true; // whether to flip the webcam
    webcam = new tmImage.Webcam(200, 200, flip); // width, height, flip
```

Figure 5 Source code snippet for upload on google cloud

b. Web View Results

After all the source code and models have been uploaded to Google Cloud Source with a link to access the model from TensorFlow.js. Here's what it looks like:

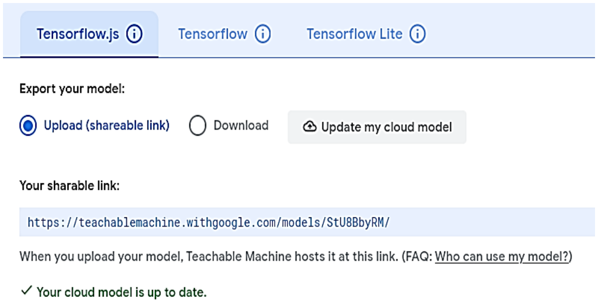

Figure 6. View of results

Figure 6 above shows a web display that has been successfully created and is ready to use for each class of rice types classifier. The class has entered data that is ready to be trained, in the form of data sets that have been aggregated so that the data sets become more numerous. After conducting training, then new data input was carried out again in the form of file data input and data input from cameras connected to the device used to access Google Cloud. From this treatment, quite good and maximum results were obtained. In testing, the model can accurately read file data inputs and camera inputs, with an accuracy confidence rate of 96% to 99%.

The following is a display of the test image with new data input in the form of a set file and data input from the camera on the hardware that accesses the google cloud:

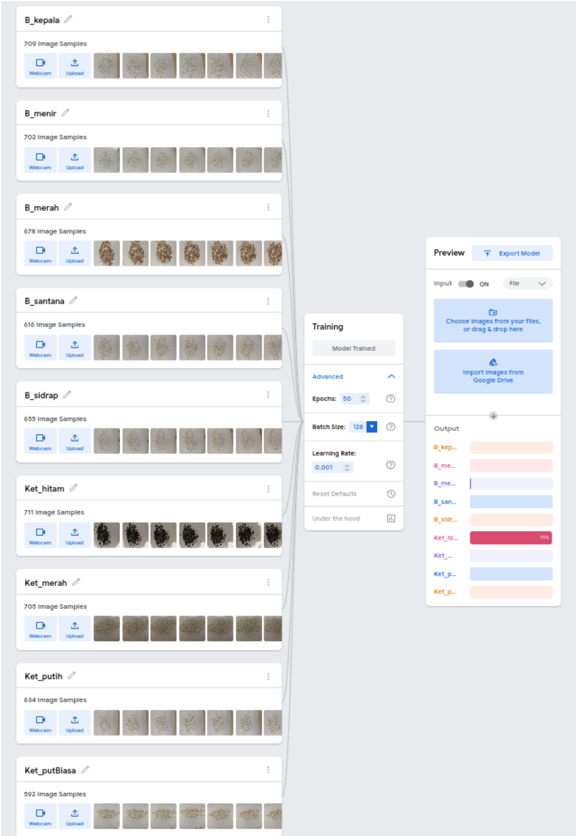

Figure 7. Rice type classification test results with file input

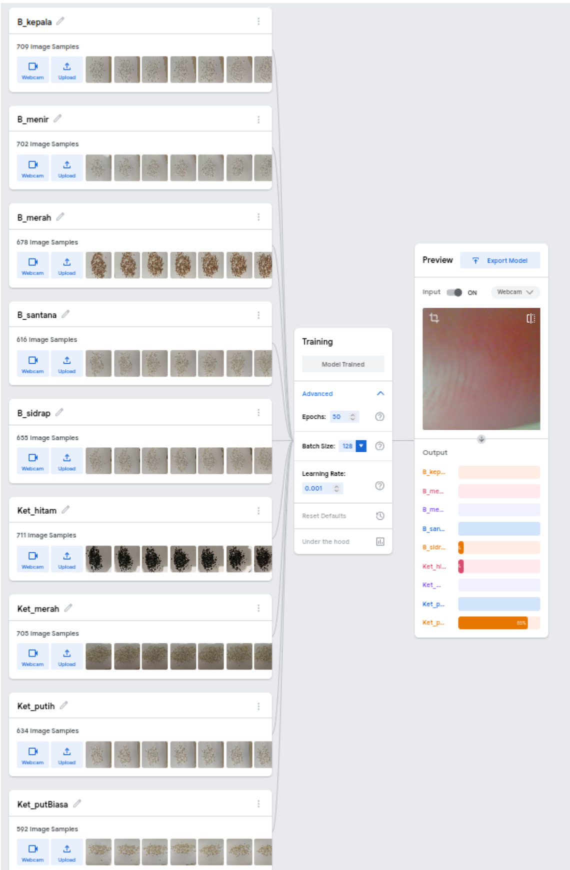

Figure 8. Rice type classification test results with camera input

Table 1. Level of confidence in the accuracy of the classification of rice types as model test results

No	Types of Rice	Input Settings	Number of images	Accuracy Confidence Level (%)
1	Head Rice	*Epochs* = 50 *Batch Size* = 128 *Learning rate* = 0,001	709	98
2	Groats Rice		702	96
3	Brown Rice		678	97
4	Santana Rice		616	97
5	Sidrap Rice		655	97
6	Black Glutinous Rice		711	99
7	Red Glutinous Rice		705	99
8	White Glutinous Rice		634	97
9	Ordinary White Glutinous Rice		582	96
Total Image			5992	
Average percentage of accuracy confidence				97,33

Based on Table 1, it can be seen that the average percentage for the level of confidence in the accuracy of the file input and the camera input in the test results, reaches 97.33%, depending on the level of quality of the input image including the lighting around the camera used. Camera input, still using only the front camera from the device. It can also be seen that the images of Black Glutinous Rice and Red Glutinous Rice reach a confidence level of 99% which indicates that the color of the rice also has an effect on determining the confidence level of the model. The shape of glutinous rice has different grains of rice than ordinary rice in general or has distinctive visual features, which allows for a high level of confidence in the test result model. In addition, the amount of data set of images of the type of rice that is included is also very influential. Then, the results of the accuracy confidence level on the test in the web browser worked well and gave quite good and accurate results. The percentage of confidence level reaches 98% to 100%, with an average accuracy of 99%. Here's a snippet of the test on the web brochure:

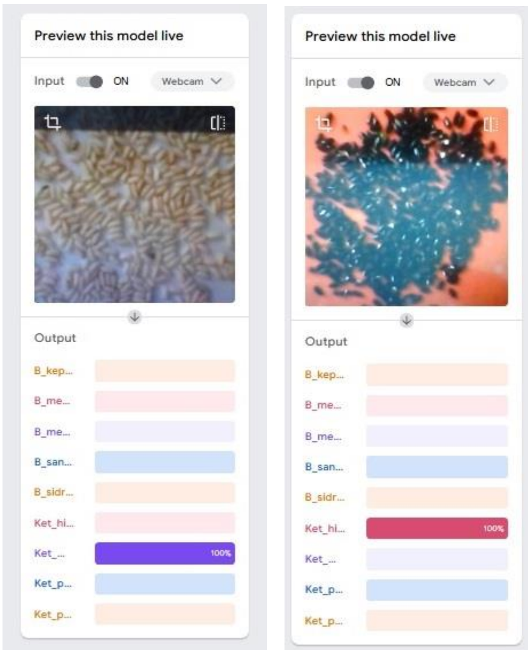

Figure 9. Web browser view on Brown Rice and Black Rice test (sample)

The following is a table of test results for all types of rice on a web browser

Table 2. Confidence level of classification accuracy of rice type results web browser

No	Types of Rice	Accuracy Confidence Level (%)
1	Head Rice	99
2	Groats Rice	98
3	Brown Rice	100
4	Santana Rice	100
5	Sidrap Rice	98
6	Black Glutinous Rice	100
7	Red Glutinous Rice	100
8	White Glutinous Rice	98
9	Plain White Rice	98
Average percentage of accuracy confidence		99

The rice type classification model created in the form of a web browser shows the ability to accurately determine the level of accuracy confidence in each type of rice tested. It can be seen from Table 2 that the average percentage for the level of confidence in the accuracy of test results on web browsers, reaches 99%, this depends on the level of quality of the input image including the lighting around the camera on the hardware used.

According to the test results on the web browser as shown in Table 2, it can be seen that the images of Brown Rice, Santana Rice, Red Glutinous Rice and Black Glutinous Rice reach a confidence level of 100% which indicates that the color of the rice and the shape of the rice grain structure which has distinctive visual features, are very influential in determining the confidence level of the model. In addition, the amount of rice type image set data entered was also highly influential, which allowed for a high level of confidence in the test result model in a web browser. This is a graph image comparing the test results, the level of confidence in accuracy, between the test results of the model and the test results of the web browser

Overall, the classification of rice types and quality with variations in yield percentages is caused by several factors, namely: (1) The quality of the video or image where the image extracted from the video has variations in lighting, shooting angle, and resolution. If, the distribution of image categories is unbalanced, the model tends to better recognize categories with more data. So, some types of rice, for example, white glutinous rice and ordinary white glutinous rice, or Santana Rice, Sidrap Rice, Head Rice may have very similar visual features, so it is difficult to distinguish them by the model, especially with a limited number of datasets, and (2) evaluation of real conditions, when the application is used in real conditions, the images taken may differ from the training data in some aspects such as lighting, background, or shooting angle resulting in a decrease in the percentage of confidence of the developed model

The model, which was developed by utilizing this CNN-based teachable machine, is able to produce a fairly high level of accuracy. In the model test, the accuracy level of confidence was obtained ranging from 96% to 99% with a total average confidence level of 97.33%. And when tested on the web bowser, an accuracy confidence level was obtained between 98% to 100%, with an average accuracy confidence level of 99%.

The CNN-based method is said to be able to produce a high level of accuracy in object classification. Research shows that the model has been developed achieves excellent and accurate performance in a variety of visual tasks, including object classification and detection, thanks to its ability to extract strongly discriminatory features from image data [44]. In addition, CNNs have also been shown to be more efficient compared to other classification methods, such as Support Vector Machines (SVMs) and Multi-Layer Perceptrons (MLPs), in handling complex real-world data [45]. CNNs also excel not only in the classification of obvious objects, but also in more challenging situations, such as the classification of obstructed or hidden objects [46]. The use of techniques such as object-based image processing (OBIA) in combination with CNNs has shown a significant increase in accuracy in image mapping and classification [19]. CNNs can be further optimized with transfer learning techniques and convolutional scale mergers to improve classification accuracy in various applications [47]. Thus, CNN's superiority in object classification lies not only in the high accuracy achieved, but also in its flexibility and ability to adapt to different types of data and classification challenges. This makes CNN a very valuable tool in the field of image processing and artificial intelligence [48].

IV. CONCLUSION

The performance model developed for rice classification with a browser is very accurate in expressing confidence in the accuracy of various types of rice. In the model test, with file data input and camera input, the model accuracy confidence level reached 96% to 99%, with the average percentage for the accuracy confidence level on both file input and camera input, reaching 97.33%. Then, the results of the accuracy confidence level on the test in the web browser worked well and gave quite good and accurate results. The percentage of confidence level reaches 98% to 100%, with an average accuracy of 99%. According to the test results on the web browser, it can be seen that Brown Rice, Santana Rice, Red Glutinous Rice and Black Glutinous Rice reach a 100% confidence level which indicates that the color of the rice and the shape of the rice grain structure which has distinctive visual features, are very influential in determining the confidence level of the model. In addition, the amount of rice type image set data entered was also highly influential, which allowed for a high level of confidence in the test result model in a web browser.

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