Application of Convolutional Neural Network (CNN) Using TensorFlow as a Learning Medium for Spice Classification

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***Abstract*— The purpose of this research are: (1) To determine the accuracy of the CNN method in the development of a website for classifying spices, (2) To assess the feasibility of the spice classification websiteas a learning medium, (3) To ascertain user responses to the spice classification website as a learning medium. The method employed in this research is research and development. This study utilizes the ADDIE development method, which comprises 5 stages: (1) Analysis, (2) Design, (3) Development, (4) Implementation, and (5) Evaluation. The research yielded a significantly high accuracy rate. This is demonstrated by the results showing an accuracy of 96%, precision of 97%, and recall of 96%. Moreover, the research found the developed website to be feasible. This is supported by the evaluation using the Learning Object Review Instrument (LORI), resultingin a score of 88% from media experts and a score of 90% from subject matter experts. Additionally, user response was positive. This is evidenced by testing thelearning media on 10th-grade culinary students from SMK N 4 Surakarta, which yielded a score of 76% using the System Usability Scale (SUS), indicating a favorable usability assessment. In conclusion, the spiceclassification website, as a learning medium, can be employed as a suitable educational tool.**

***Index Terms*— Convolutional Neural Network (CNN); Development; Learning; Spices; TensorFlow; Website**.

I. INTRODUCTION

As we know, Indonesia is a country rich n spices. These spices can be used as a source of healthy food ingredients. However, over time, spices have been overshadowed by fast food or so-called junk food. Consequently, the current generation is less familiar with spices. Therefore, in this article, we will explore the effects or benefits of various types of spices on physiological functions withinthe body.

Indonesia is a country abundant in spices. There are various types of spices in Indonesia, and their usage has long been practiced within the community. Spices are widely used in the pharmaceutical and food industries, among others [1]. Contemporary lifestyles have led the Generation Z to be less acquainted with Indonesia's natural wealth, namely spices [2].

The concern of Generation Z towards spices is diminishing due to their inclination towards instant and fast items such as fast food or junk food. Consequently, the utilization of spices as cooking ingredients or for medicinal purposes has become less common. As a result, Generation Z is no longer familiar with the benefits and properties inherent in spices, and even worse, manyyoungsters are unfamiliar with the various types of spices around them [3]. Recognizing the different types of spices poses a challenge for the millennial generation. Some spices mayappear similar at first glance without knowing their characteristics. Based on a survey conducted in this study, involving 100 respondents attempting to identify five types of Indonesian spices, only 31% of respondents accurately identified more than three types of spices [4].

Generation Z is more interested in smartphones than in learning traditional knowledge. However, smartphones can alsoserve as highly effective learning tools. Educators and learners, when exposed to digital technology systems, are motivatedwhen they perceive benefits from such technological systems [5]. Utilizing smartphones has several advantages. One ofthem is their internet connectivity. Creating teaching materials through digital technology can be more engaging and motivating, as content can be presented not only through text but also through images, audio, video, and animations, influencing improved learning behavior [5]. This facilitates access to and implementation of various knowledge fields widely available. Moreover, smartphones enable learning anytime and anywhere, irrespective of time and place. These affordable devices are accessible to the general public.

The literature review encompasses several studies related to the application particularly TensorFlow, in various domains. "Implementation of TensorFlow-based deep learning in the learning application of around things in English" by Heru Budianto et al., they introduces a learning application aimed at teaching English to children by recognizing objects in their environment using TensorFlow. However, this study primarily focuses on language learning rather than object classification [17]. In contrast, our research targets spice classification, providing a unique application of TensorFlow in a specific domain.

In another study titled “Machine learning in medicine using JavaScript: building web apps using TensorFlow.js for interpreting biomedical datasets” Jorge G. Pires discusses the utilization of TensorFlow.js for interpreting biomedical datasets, achieving high accuracy in tasks like diabetes detection and surgery complications prediction [18]. While this study demonstrates the effectiveness of TensorFlow.js in medical applications, it does not directly relate to our research on spice classification. Our study addresses a different domain, focusing on image classification for spice recognition rather than medical data analysis.

Then, Noor Mohd Ariff Brahin et al. present "LearnWithIman" in “Development of vocabulary learning application by using machine learning technique,” a vocabulary learning application for children using TensorFlow object detection API. Similar to Budianto et al., this study emphasizes language learning through object recognition but targets a different audience and language [19]. Our research, however, concentrates on spice classification, offering a distinct application of TensorFlow in educational technology.

Other than that, Sona Saitou et al. (2018) apply TensorFlow to recognize characteristic structures in fragment molecular orbital (FMO) calculations in “Application of TensorFlow to recognition of visualized results of fragment molecular orbital (FMO) calculations.” Although this study shares the use of TensorFlow for pattern recognition, it deals with molecular structures rather than object classification [20]. Our research diverges from this by focusing on image classification for spice identification, showcasing the versatility of TensorFlow in various fields.

Lastly, Haim A Abenhaim (2023) develops an object detection application for a forward collision early warning system using TensorFlow Lite in “Object Detection Application for a Forward Collision Early Warning System Using TensorFlow Lite on Android.” While this study employs TensorFlow for object detection, it is oriented towards automotive safety rather than spice classification [21]. Our research explores a different application domain, demonstrating the adaptability of TensorFlow in diverse contexts.

In summary, while existing literature demonstrates the versatility of TensorFlow in various domains such as language learning, medical diagnostics, and object detection, there remains a gap in the application of this technology specifically for spice classification. Our research addresses this gap by employing TensorFlow for image classification in the context of spice recognition, offering a novel contribution to the field of applications.

The introduction of spice types can utilize deep learning techniques. Deep learning involves processing data using artificial neural networks. This algorithm takes data as input and processes it through hidden layers. Subsequently, the algorithm performs nonlinear transformations on input data to generate output values. A widely used deep learning technique is Convolutional Neural Network (CNN), capable of recognizing spice types. Hence, in this study, the researcher will employ a website-based Convolutional Neural Network (CNN) method. Several studies on image processing using CNN have yielded high accuracy rates. For instance, a study conducted by Wulandari, Yasin, Widiharih, and Statistika on Classification Of Digital Images Of Spices Using Convolutional Neural Network (Cnn). achieved an accuracy rate of 88.89% [6].

Based on the aforementioned background, many people are still unfamiliar with the various spices in Indonesia, necessitating technology to facilitate their recognition. The utilization ofthe CNN algorithm can be used for classification. Therefore, this research aims to perform website- based spice classification using the CNN algorithm.

II. RESEARCH METHOD

The research method I am using in this study is the Research and Development (R&D) method. R&D, or Research and Development, is a research approach used to develop and test products that will be appliedin the field of education [7]. Utilizing the ADDIE approach, which stands for Analysis,Design, Develop, Implement, and Evaluate. The ADDIE model is employed to establish a foundation for performance in the learning process, by implementing the concept of developing learning product designs [8]. Thisstudy employs a questionnaire adapted from the Learning Object Review Instrument (LORI). The material being assessed covers several aspects, namely content quality, learning goal alignment, feedback and adaptation, and motivation.

The application, tools and library I will use is as follows:

Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a type of neural network that is specialized for processing data with a grid structure, such as two-dimensional images. The term "convolution" refers to a linear algebraic operation involving matrix multiplication between the filter and the image being processed. This process takes place in convolutional layers, which are one of several types of layers that can exist in a network. Convolution layers are the main and critical component of CNN. In addition to the convolution layer, another type of layer that is often used is the Pooling Layer, which is used to take the maximum or average value of the pixels in the image parts. The following is an example of a CNN architecture.

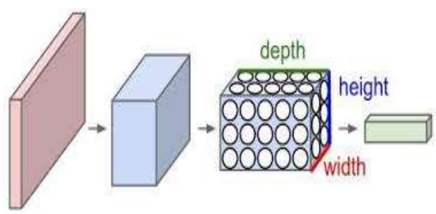

Fig 1. Neural Network Structure

The figure above shows that each input layer that is entered has a different volume and is represented by depth, height and width. Each quantity obtained depends on the previous layer's filtration results and the number of filters used. The network models have proven effective in dealing with image classification problems [11].

The function of CNN is to process data in the form of multiple arrays. There are three layers or layers in CNN, namely the Convolutional Layer, the Pooling Layer, and the Fully Connected Layer. An illustration of the CNN architecture is shown in Figure 2.

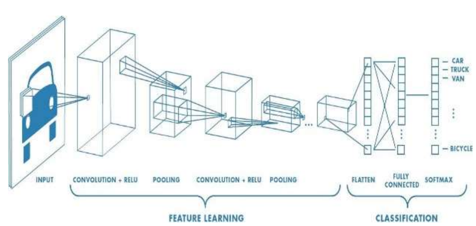

Fig 2. CNN Architecture

Input Layers

In this layer, CNN will store the pixel value of the input image. In general, each image has a different size. For example, an image with a size of 224x224 and 3 color channels Red, Green, Blue (RGB) will be used as input for CNN in the form of an array with a size of 224x224x3.

Convolution Layers

The Convolution Layer is the first component in CNN. This layer performs convolution between the input image with predetermined filters without changing the structure of the original image. The function of the convolution layer is to extract features from the image to be used in model training [12]. An example image of the convolutional layer is shown in Figure 3.

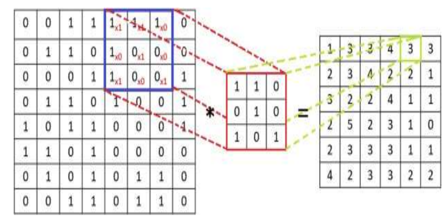

Fig 3. Convolution Layer

The Convolution Layer performs a process that produces a new image that contains extracted features from the input image. This process uses a filter (kernel) in the form of a 2-dimensional array with a size of 5x5, 3x3, or 1x1. Each image passes through the filter, resulting in a feature map. The result of the feature map from this layer is then used in the next layer, namely the Activation Function.

Pooling Layer

Pooling layer is the process of reducing the number of parameters and number of calculations in the network, as well as preventing overfitting of the image. This layer is divided into average pooling and max pooling. Average pooling is taking the average value of the selected area, while max pooling is taking the largest value of the selected area [12].

The pooling layer is a screen that utilizes the feature map function as an input and then processes it with various statistical operations that have been implemented by the system being managed. This pooling is a layer that is used sequentially in a CNN architecture in a progressive manner. The purpose of using this pooling layer is to take the max pooling or average value of parts of the image. The use of pooling layers is to reduce the size of the image so that it can be easily replaced with another layer, namely the convolution layer [13].

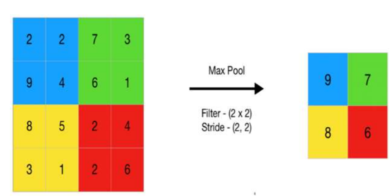

Fig 4. Pooling layer

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Rectified Linear Units (RELU)

Rectified Linear Unit (RELU) is an activation function that has the advantage of being able to process large data quickly, which is used between the convolutional layer and the pooling layer. RELU maintains the results of the convolution image in a positive definite domain, so that every negative value that comes from the convolution process will go through the RELU process, and make the negative value equal to 0 [12].

$$f = \max(0, x)$$

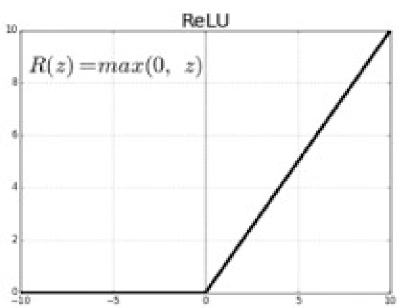

Fig 5. Curve of ReLu function

Softmax

Softmax is an activation function that is often used in neural networks that have many output categories (multi-class). The softmax function changes calculated values into probability values, this makes the calculated values comparable. By using the softmax function, it can be seen which class has the greatest possible value. Then, the biggest possibility will be the selected class and the next input will be classified into that class [12].

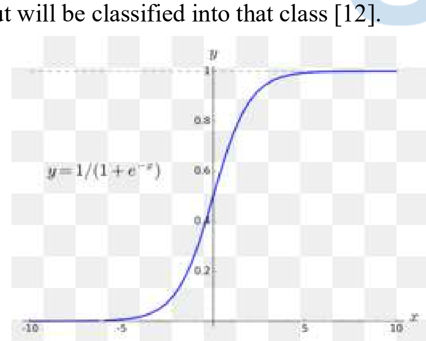

Fig 6. Curve of ReLu function

Fully Connected Layer

Fully Connected Layer is part of the neural network architecture where all data will be converted into one dimension. This process is known as flatten, which changes the dimensions of the data. This layer consists of nodes that are interconnected, and have weights and activation functions. The output of this layer is a prediction based on input data [12].

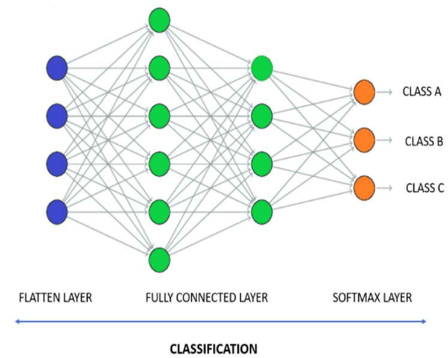

Fig 7. Fully Connected Layer

Confusion Matrix

Confusion matrix is a tool used to evaluate a classification model with the aim of estimating the truth or error of objects. This is in the form of a matrix of predictions that will be compared with the original input class or in other words, contains information about the actual and predicted values in the classification [16]. The Confusion Matrix is a way to assess the performance of a classification model, namely through the accuracy of the model. Some terms that are important in determining the level of accuracy are true positive (TP), true negative (TN), false positive (FP), and false negative (FN). These terms are usually combined in a matrix known as a confusion matrix, as shown below [14].

Predicted Values \ Actual Values	Positive (1)	Negative (0)
Positive (1)	TP	FP
Negative (0)	FN	TN

Fig. 8 Confusion Matrix

The accuracy value in classification is the percentage of accuracy of data records that are classified correctly after testing the classification results. Calculation of accuracy with the confusion matrix is as follows.

Accuracy = (TP+TN) / (TP+FP+FN+TN)

Tensorflow

TensorFlow, a freely available open-source software library, serves multiple purposes, with its primary emphasis being on neural network training and inference. This library operates on a dataflow model and utilizes programming techniques [15].

The sampling technique used in this research is Random Sampling Technique, in which the sample determination technique ensures that each analytical unit has an equalchance and is considered to represent a population.

The data I will use for this study isobtained from two sources. The first source is data collection conducted by AwalTry (2020),which can be accessed from the website https://www.kaggle.com/datasets/awaltry/re mpah. The second source involves manualdata collection using a smartphone. From theabove data, it is divided into 500 training data,100 validation data, and 25 test data.

In the application of the convolutional neural network method for classifying spices, Confusion Matrix is employed. Confusion Matrix is a technique used to calculate accuracy in the context of data mining [9]. The Confusion Matrix is a table that represents the classification of the correct and incorrect test data.

An example of a Confusion Matrix for binary classification is shown as follow.

TABLE I. CONFUSION MATRIX

		Prediction	
		Positive	Negative
Class	Positive	TP	FP
	Negative	FN	TN

Explanation:

TP (True Positive) = Positive data correctlypredicted.

TN (True Negative) = Negative data correctly predicted.

FP (False Positive) = Negative data incorrectly predicted as positive.

FN (False Negative) = Positive data incorrectly predicted as negative.

Confusion matrix formulas to calculate accuracy, precision, and recall are as follows:

- Accuracy is a measure of how accurate a model is in predicting correct outcomes. It is calculated by dividing the total correct predictionsmade by the model by the total number of predictions made.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

- Precision is a measure of how accurately a model predicts positive outcomes. It is calculated by dividing the number of true positives (correct positive predictions) by the total number of positive predictions made by the model.

Precision = TP / (TP + FP)

- Recall is a measure of how accurately a model detects all positive occurrences. It is calculated by dividing the number of true positives (correct positive predictions) by the total number of actual positive occurrences.

Recall = TP / (TP + FN)

Since this study uses the SUS (System Usability Scale) method, the data analysis technique employed will use the SUS score calculation formula. For each respondent, it can beformulated as follows:

- For each odd-numbered question (1, 3,5, 7, 9), subtract 1 from the score (X-1).
- For each even-numbered question (2, 4,6, 8, 10), subtract its value from 5 (5-X).

Add the values of the even and odd-numbered questions. Then multiply the sum by 2.5. By following the procedures explained earlier, you can calculate the SUS score for eachrespondent and then calculate the averagescore to obtain the overall SUS score.

III. RESULT

An evaluation was conducted on the accuracy of the created model using aconfusion matrix. After the data processing is completed, the Confusion Matrix is employedfor evaluation, revealing the values of TP, TN, FP, and FN for each class. This yields accuracy, precision, recall, and f1-score values.

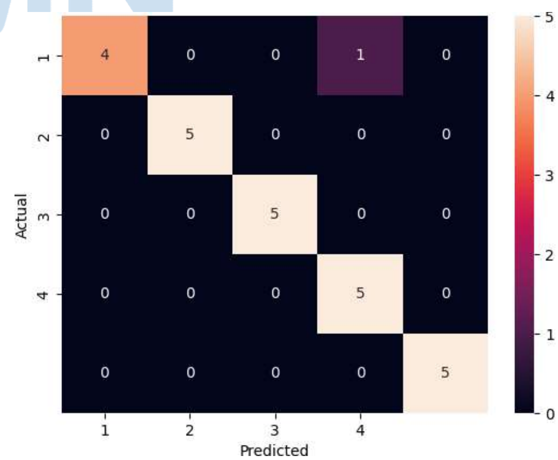

Fig 9. Confusion Matrix's Result

TABLE II. CONFUSION MATRIX'S RESULT

Class	*True Positive (TP)*	*False Positive (FP)*	*False Negative (FN)*
Jahe	4	0	1
Kencur	5	0	0
Kunyit	5	0	0
Lengkuas	5	1	0
Temulawak	5	0	0

```
              precision    recall  f1-score   support

           0       1.00      0.80      0.89         5
           1       1.00      1.00      1.00         5
           2       1.00      1.00      1.00         5
           3       0.83      1.00      0.91         5
           4       1.00      1.00      1.00         5

    accuracy                           0.96        25
   macro avg       0.97      0.96      0.96        25
weighted avg       0.97      0.96      0.96        25
```

Fig 10. Accuracy,Precision,Recall,F1-Score

1. Accuracy

Based on the above figure, it can be observedthat the evaluation results of the model using theconfusion matrix approach have an accuracy value of 0.96, indicating that the model is sufficiently suitable for use.

2. Precision

TABLE III. PRECISION RESULT EACH CLASS

Class	Precision
Jahe	1,00
Kencur	1,00
Kunyit	1,00
Lengkuas	0,83
Temulawak	1,00

The precision score is computed by comparing the number of correct positive predictions to the total number of positive predictions. The evaluation outcomes presented in the table above reveal the precision scores for individual classes as well as the overall precision score.

$$\text{Precision} = \frac{\text{P(Jahe)} + \text{P(Kencur)} + \text{P(Kunyit)} + \text{P(Lengkuas)} + \text{P(Temulawak)}}{\text{Sum of Class}}$$

$$\text{Presisi} = \frac{1{,}0 + 1{,}0 + 1{,}0 + 0{,}83 + 1{,}00}{5}$$

$$\text{Presisi} = 0{,}97$$

3. Recall

TABLE IV. Recall Result Each Class

Class	Recall
Jahe	0,80
Kencur	1,00
Kunyit	1,00
Lengkuas	1,00
Temulawak	1,00

The Recall value, also known as sensitivity, represents the proportion of accurate positive predictions in relation to the overall true positives within the dataset. Examining the data table presented earlier, we can see that the sensitivity values for different classes are as follows: 0.8 for the Ginger class, 1.00 for the Lesser Galangal class, 1.00 for the Turmeric class, 1.00 for the Galangal class, and 1.00 for the Javanese Ginger class.

$$Recall = \frac{\text{R(Jahe)} + \text{R(Kencur)} + \text{R(Kunyit)} + \text{R(Lengkuas)} + \text{R(Temulawak)}}{\text{Sum of Class}}$$

$$Recall = \frac{0{,}8 + 1{,}0 + 1{,}0 + 1{,}0 + 1{,}0}{5}$$

$$Recall = 0{,}96$$

4. F1-Score

The F1-Score represents an average of precision and recall, as indicated in the table above. In the case of the Ginger class, where Precision is 1.00 and Recall is 0.8, the F1 Score is calculated to be 0.89. Similarly, for the Lesser Galangal class, where Precision is 1.00 and Recall is 1.00, the resulting F1 Score is 1.00. The Turmeric class, with a Precision of 1.00 and Recall of 1.00, also yields an F1 Score of 1.00. As for the Galangal class, which has a Precision of 0.83 and Recall of 1.00, the computed F1 Score is 0.91. Lastly, for the Javanese Ginger class, having a Precision of 1.00 and Recall of 1.00 results in an F1 Score of 1.00.

IV. DISCUSSION

After testing using the confusion matrix, an average precision value of 97% was obtained. The average Recall value is 96%. And an accuracy of 96% was achieved. The results above indicate that the outcomes obtained are quite favorable in terms of accuracy, precision, and recall. This is demonstrated by comparing them with the research conducted by Evan Tanuwijaya andAngelica Roseanne in "Modification of

VGG16 Architecture for Classification of Indonesian Spices Digital Images." In that study, an accuracy rate of 85%, recall value of 80%, and precision value of 84% were obtained using the VGG16 base model [10].

TABLE V. Comparison Result

	Researcher Results	Previous Research Results
Accuracy	96%	85%
Precision	97%	84%
Recall	96%	80%

The researcher's results in the table are higher because the researcher used a larger dataset, specifically 500 training data,compared to the previous researcher whoonly used 100 training data.

Development Stage

During the development stage, the process began with creating a CNN model for classifying spices on the developed website. Firstly, the necessary libraries were imported, followed by preparing the dataset, including dividing it into classes and pre-processing the data. Subsequently, the CNN architecture was designed, with researchers opting for a custom-built model without adding a base model to it. Then, the data underwent training using the previously created model. Researchers utilized Google Colab for training the data due to its superior specifications for such tasks. Once the training was completed, the model was saved in .h5 format for implementation into the spice classification learning website.

Implementation Stage

During the implementation stage, the model was integrated into the website. The first step involved creating the website's interface, with researchers using a Bootstrap template. Next, researchers customized several aspects of the interface and added desired features. After designing the website's interface, researchers implemented the model using the Flask framework in Python and connected the back end with the front end. Lastly, the researchers uploaded the completed website to hosting to make it accessible to everyone.

Model Evaluation

After testing using a confusion matrix, the model yielded an average precision score of 97%, an average recall score of 96%, and an accuracy of 96%. These results indicate that the obtained outcomes are quite satisfactory in terms of accuracy, precision, and recall.

Evaluation of Spice Classification Learning Website

The media expert validation was conducted by an individual proficient in the field of learning media. The assessment instrument comprised four aspects: Presentation Design, Interaction Usability, Accessibility, and Reusability. The expert's evaluation resulted in a total score of 88 and an average score of 4.4, indicating an excellent rating.

The content expert validation was conducted at SMK N 4 Surakarta by experts in kitchen spices. The validation instrument consisted of 12 assessment points divided into four aspects: Content Quality, Learning Goal Alignment, Feedback and Adaptation, and Motivation. Overall, the validation results showed that the website received a total score of 54 and an average score of 4.5, indicating an excellent rating.

Thirty-two students from SMK N 4 Surakarta's culinary department participated in the usability test. After the test, the participants were asked to fill out a questionnaire assessing their response to the learning media. The questionnaire consisted of 10 assessment points. The results indicated that the students gave a total score of 76.4 and an average score of 30.56, indicating a good rating.

V. CONCLUSION

Based on the research findings, it can be concluded that the developed spice classification learning website is deemed suitable for use. Additionally, there are several strengths and weaknesses identified for further website improvement in future research.

Strengths:
1. The website can be accessed on various devices and screen resolutions.
2. Attractive website interface.
3. Comprehensive content.
4. High classification accuracy.

Weaknesses:
1. The website is still static.
2. Limited number of classes.
3. Lack of error handling mechanisms.

The use of the CNN method for classifying spices through a website-based learning media results in a relatively high accuracy rate of 96%. This figure is considered sufficient for implementation within the spice classification learning media website. With such a high accuracyresult, the classification process within the spice classification website can perform well. This spice classification website can serve as an effective means to enhance understanding and mastery of concepts taught in the subject of spice introduction. With the presence of this technology, teaching and learning become more innovative, enjoyable, and provide significant benefits for learners.

REFERENCES

[1] Hambali, E., & Permanik, R. (2006). *Membuat Bumbu Instan Kering*. Penebar Swadaya Grup.

[2] Sinatra, C., Damajanti, M. N., & Milka, R. M. (2016). Perancangan Buku Pengenalan Rempah-rempah bagi Masyarakat Modern.*Jurnal DKV Adiwarna*, *2*(9), 9.

[3] Hikmatulloh, E., Lasmanawati, E., &Setiawati, T. (2017). Manfaat Pengetahuan Bumbu Dan Rempah Pada Pengolahan Makanan Indonesia Siswa Smkn 9 Bandung. *Media Pendidikan, Gizi, Dan Kuliner*, *6*(1).

[4] Putra, A. E., Naufal, M. F., & Prasetyo, V. R. (2023). Klasifikasi Jenis Rempah Menggunakan Convolutional Neural Network dan Transfer Learning. 9(1), 12–18.

[5] Muhasim, M. (2017). Pengaruh Tehnologi Digital terhadap Motivasi Belajar Peserta Didik. *Palapa*, *5*(2), 53–77. https://doi.org/10.36088/palapa.v5i2.46.

[6] Wulandari, I., Yasin, H., Widiharih, T., Statistika, D., & Diponegoro, U. (2020). Klasifikasi citra digital bumbu dan rempah dengan algoritma convolutional neural network (cnn) 1,2,3. 9, 273–282.

[7] Maydiantoro, A. (2020). Model Penelitian Pengembangan. *Chemistry Education Review (CER)*, *3*(2), 185.

[8] Hidayat, F., & Nizar, M. (2021). Model Addie (Analysis, Design, Development, Implementation and Evaluation) Dalam Pembelajaran Pendidikan Agama Islam. *Jurnal Inovasi Pendidikan Agama Islam (JIPAI)*, *1*(1), 28–38.https://doi.org/10.15575/jipai.v1i1.1104.

[9] Pratiwi, B. P., Handayani, A. S., & Sarjana, S. (2021). Pengukuran Kinerja Sistem Kualitas Udara Dengan Teknologi Wsn Menggunakan Confusion Matrix. *Jurnal Informatika Upgris*, *6*(2), 66–75. https://doi.org/10.26877/jiu.v6i2.6552.

[10] Tanuwijaya, E., & Roseanne, A. (2021). Modifikasi Arsitektur VGG16 untuk Klasifikasi Citra Digital Rempah- Rempah Indonesia Classification of Indonesian Spices Digital Image using Modified VGG 16 Architecture. *Jurnal Manajemen, TeknikInformatika, Dan Rekayasa Komputer*, *21*(1), 191–198. https://doi.org/10.30812/matrik.v21i1.xxx.

[11] Yunanto, R., Purfini, A. P., & Prabuwisesa, A. (2021). *Survei Literatur : Deteksi Berita Palsu Menggunakan Pendekatan Deep Learning*. *xx*, 118–130. https://doi.org/10.34010/jamika.v11i2.493

[12] Budi, R. S., Patmasari, R., & Saidah, S. (2021). KLASIFIKASI CUACA MENGGUNAKAN METODE CONVOLUTIONAL NEURAL NETWORK (CNN) WEATHER CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK (CNN) METHOD. 8(5), 5047–5052.

[13] Mustafi, K., Prima, A., Dimas, N., & Arya, M. (2022). *Klasifikasi sampah menggunakan Convolutional Neural Network*. *3*(2), 72–81. https://doi.org/10.56705/ijodas.v3i2.33

[14] Wulandari, I., Yasin, H., Widiharih, T., Statistika, D., & Diponegoro, U. (2020). Klasifikasi citra digital bumbu dan rempah dengan algoritma convolutional neural network (cnn) 1,2,3. 9, 273–282.

[15] Primatama, Y., Rhamadani, A. E., Ramtomo, F. D., Cahya, D., & Buani, P. (2018). *Menggunakan Pemindai Wajah Berbasis Android*. 59–65.

[16] Nawangsih, I., Melani, I., Fauziah, S., & Artikel, A. I. (2021). Pelita Teknologi Prediksi Pengangkatan Karyawan Dengan Metode Algoritma C5.0 (Studi Kasus Pt. Mataram Cakra Buana Agung. *Jurnal Pelita Teknologi*, *16*(2), 24–33.

[17] H. Budianto, T. Khalimi, R. Ismaya, E. Kurniadi, and E. Dharmawan, “Implementation of tensor flow-based deep learning in the learning application of around things in English,” J. Phys. Conf. Ser., vol. 1933, no. 1, p. 012007, 2021.

[18] J. G. Pires, “Machine learning in medicine using JavaScript: building web apps using TensorFlow.js for interpreting biomedical datasets,” bioRxiv, 2023.

[19] N. Mohd Ariff Brahin, H. Mohd Nasir, A. Zakwan Jidin, M. Faizal Zulkifli, and T. Sutikno, “Development of vocabulary learning application by using machine learning technique,” Bull. Electr. Eng. Inform., vol. 9, no. 1, pp. 362–369, 2020.

[20] S. Saitou et al., “Application of TensorFlow to recognition of visualized results of fragment molecular orbital (FMO) calculations,” Chem-Bio Inf. J., vol. 18, no. 0, pp. 58–69, 2018.

[21] B. Satya, Hendry, and D. H. F. Manongga, “Object detection application for a forward collision early warning system using TensorFlow lite on android,” in Third Congress on Intelligent Systems, Singapore: Springer Nature Singapore, 2023, pp. 821–834.