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Implementation of Convolutional Neural Networks (CNN) in An Emotion Detection System for Measuring Learning Concentration Levels

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A B S T R A C T

Technological advancements have had a significant impact on the education sector, including the application of Convolutional Neural Networks (CNN) for facial image analysis. This research aims to implement CNN to measure students' learning concentration levels. The FER2013 dataset, which includes seven emotion classifications and comprises 28,709 images for training data, is used as the database. The data is processed through rescaling and augmentation to prepare the CNN model. The model consists of several convolutional layers, pooling layers, and fully connected layers designed to extract crucial features from facial images. Evaluation results demonstrate a very high accuracy of 94.95% on training data, indicating that the model effectively recognizes complex patterns within the data. Although there is a higher loss value of 157% and a decreased accuracy of 62.75% on validation data, this suggests that the model possesses a strong foundational capability and can still be improved through further adjustments. With high accuracy in training and promising validation results, the model shows substantial potential for real-world application, where it can assist teachers in understanding students' emotional responses in real-time. The implementation of CNN aids educators in comprehending students' emotional responses and adapting their teaching methods more effectively, thereby creating a more conducive learning environment and enhancing students' academic and social development. These findings also open opportunities for further research to improve the performance and generalization of the model on unseen data, making this technology an increasingly reliable tool in education.

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1. Introduction

At present, humans are highly dependent on technology, making it a fundamental necessity. From children to adults, professionals to the general public, technology is utilized in various aspects of their lives. The advancement of technology inevitably impacts the field of education. Global demands require the education sector to continuously adapt to technological progress, with a focus on enhancing the quality of education. Specifically, adapting the use of information and communication technology in the learning process has become a necessity[1].

Convolutional Neural Networks (CNN) have emerged as a leading innovation in the field of artificial intelligence, particularly in the processing and analysis of image data. Inspired by the way the human brain recognizes visual patterns, CNN methodologies have had a significant impact across various industries[2]. CNN consist of convolutional layers that identify and extract important features from image data through the processes of convolution and pooling. This innovation, initially introduced by Yann LeCun and his colleagues, has advanced computer capabilities in object recognition, image processing, and other fields reliant on visual analysis [3].

One of the main advantages of CNN is their ability to automate visual analysis, which contributes significantly to various applications. For instance, in the healthcare sector, CNN can be employed to diagnose diseases based on medical images, expediting the diagnosis and treatment processes. In the field of autonomous vehicles, this technology enables cars to recognize and respond to objects in their surroundings. Beyond that, in the security industry, CNN can be used for facial or object detection in video surveillance. [4]. The significance of CNN extends to various sectors, including agriculture. For instance, the application of this technology in the agricultural sector includes detecting high-quality fruit products and quickly and accurately identifying diseases and pests affecting those fruits[5].

The teaching and learning process in the classroom represents an interactive dynamic between the instructor and the students, during which knowledge is conveyed and absorbed [6]. The educator functions as a facilitator, delivering instructional material through creative and interactive methods, while students engage actively in the learning process through discussions, question-and-answer sessions, and group activities. In a conducive classroom environment, this process fosters the exchange of ideas, skill development, and a deep understanding of concepts, thereby creating a motivating and supportive learning atmosphere that enhances both academic and social development. This perspective is supported by existing research on classroom teaching and learning, as discussed by Werdayanti and colleagues[7] The role of the educator is crucial; therefore, it is imperative for teachers to possess the necessary competencies, skills, and proficiency in instruction.

A pleasant learning experience encompasses positive interactions between teachers and students, supportive physical conditions, and an atmosphere that creates an ideal environment for the learning process. A pleasant learning atmosphere not only prevents students from feeling bored but also alleviates their fear of engaging in the learning process[8]. In the context of learning, teachers need to create a supportive environment where students are encouraged to develop their creativity by actively asking questions, solving problems, and expressing their ideas. This approach allows students to engage actively in the learning process, rather than merely being recipients of information from the teacher. Therefore, every classroom interaction requires the use of various methods and learning models to facilitate the development of students' creativity and enhance the overall quality of learning [9].

The implementation of Convolutional Neural Networks (CNN) to measure learning concentration levels offers an innovative and efficient solution. By leveraging the capabilities of CNN in analyzing facial images and expressions, we can identify signs of concentration or boredom in students in real-time[10]. This technology not only provides a more objective evaluation but can also be used as a tool for educators to enhance their teaching methods in alignment with students' needs.

These findings are consistent with the research conducted by Esmaeili and colleagues, which concluded that it is crucial for teachers to understand that each student has their own unique characteristics. Creative and enthusiastic teachers will employ appropriate methods by observing the individual differences among students. The application of sanctions and rewards at the right moments can create a pleasant learning experience, as well as foster a positive classroom atmosphere that enhances students' enjoyment of the learning process [11].

This research aims to explore and develop a Convolutional Neural Network (CNN) model capable of measuring students' concentration levels based on facial image analysis. Through this research, it is expected that an effective approach will be identified for monitoring and enhancing the quality of student learning, while also making a positive contribution to the advancement of educational technology.

2. Method

2.1. Dataset Collection

The dataset used in this system was sourced from the FER2013 dataset [1]. The images in this dataset have a matrix size of 48x48 pixels and are in greyscale format. This dataset consists of seven emotion classification labels: anger, disgust, fear, happy, sad, surprised, and neutral. Each image is represented as a

48x48 matrix with color values ranging from 0 to 255. Below is an example of an image from the FER-2013 dataset. :

Figure 1. Example of FER-2013 Dataset Image

2.2. *Data Processing*

The collected data is divided into three parts for each class: training data, validation data, and test data. This division is performed randomly from the image data in each class of the FER2013 dataset. The training data is used to train the model, the validation data is employed to assess the model's performance during training, and the test data is utilized to measure how well the model can predict previously unseen data, ensuring that the model has good generalization capability[12]. Sample data is shown in table 1.

Table 1. Number of Image Data in the FER2013 Dataset

Class (Emotion)	**FER2013 (Training Data)**	**FER2013 (Validation Data)**
Anger	3995	958
Disgust	436	111
Fear	4097	1024
Happy	7215	1774
Sad	4830	1247
Surprise	3171	831
Neutral	4965	1233
Total	28709	7178

2.3. *Classification Technique*

The technique used for classification involves employing Convolutional Neural Network (CNN) algorithms in deep learning. This machine learning approach, with models specifically designed for classification tasks in two-dimensional media such as images, videos, text, or audio, proves highly beneficial [13]. Convolutional Neural Network (CNN) algorithms are particularly useful for detecting patterns in images and recognizing objects within them. In addition to identifying objects or items, CNNs can also classify human expressions, which traditionally required segmentation to enhance accuracy.

In general, there are three layers involved in the feature extraction process: the convolution layer, the pooling layer, and the dense (or activation) layer. These layers perform specific operations to deepen the data and identify specific image patterns.

2.3.1. *Convolution Layer*

In the convolution layer, a convolution operation is performed between the input matrix and the kernel present in the filter matrix. Convolution is an operation that involves multiplying two matrices, where the result of this multiplication is then summed. This process generates important features from the input data, which are used by subsequent layers to recognize more complex patterns and characteristics. The convolution operation aids in feature extraction, reduces data dimensionality, and enhances computational efficiency in neural networks [14].

The Convolutional Layer is crucial for shaping the depth of data within a feature. The depth of an image as input is defined by the number of channels in the image. For example, in an image of size 32x32x3, the number 3 reflects the number of color channels present in the image, which can also be considered as the image's depth. This depth is important in the learning process of CNN algorithms, where the input undergoes convolution with a set of matrices known as kernels or filters [15]. All filters are almost always square-shaped, with a depth that matches the specified dimensions.

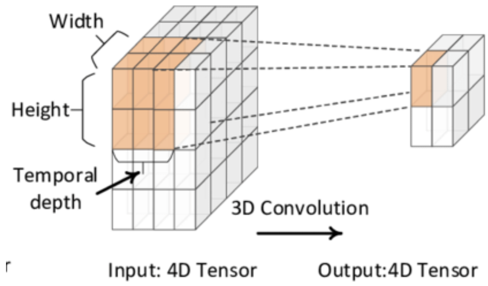

Figure 2. *Convolution Layer*

2.3.2. *Pooling Layer*

Methods for reducing the size of the input volume can be achieved in two ways: by using a convolution layer with a stride greater than 1 or by employing a pooling layer. The pooling layer is positioned after the convolution layer. Essentially, the pooling layer utilizes a filter of a specific size, which can be adjusted, and operates with a certain stride on the feature map produced by the convolution layer.

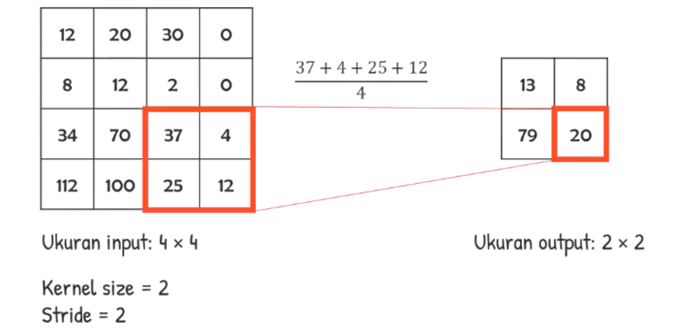

Figure 3. Pooling Layer Using Average Pooling

There are two commonly used pooling methods: average pooling and max pooling. Max pooling involves selecting the neuron with the highest activation value within each local receptive field (grid cell) and passing this highest value to the next process. In contrast, average pooling computes the output for each receptive field as the average of all activation values within that field. Both methods assist in reducing data dimensionality, thereby decreasing computational load and enhancing the efficiency of the neural network without losing important information [16].

2.3.3. *Fully Connected Layer*

The fully connected layer is a collection of neurons that are fully connected to all activations in the previous layer. After undergoing convolution and pooling processes, the data is transformed into a one-dimensional vector, which is then fed into this fully connected network. The fully connected structure can include one or more hidden layers. Each neuron in this layer multiplies its connection weights by the data from the previous layer and adds a bias. The resulting values are then passed through an activation function before being transmitted to the next layer [17].

3. Results and Discussion

3.1. System Design

System design is a description of the process flow of how this system works. [18]. The design of this system can be shown in Figure 4.

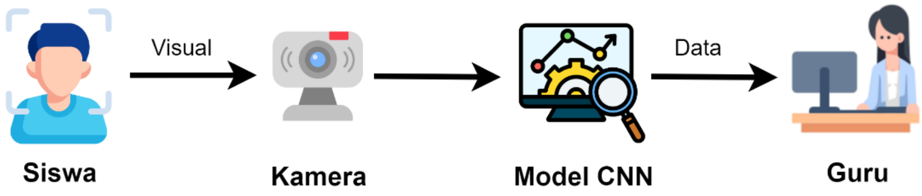

Figure 4. System Design

The system design described above illustrates that students will be recorded using a camera or webcam, which will generate visual data. This visual data will be processed by the system, focusing on the facial area. The facial data will then be analyzed using a Convolutional Neural Network (CNN), which will produce data in the form of a graph, allowing teachers to easily view and interpret the results [19].

3.2. Interface Design

The system interface design is the initial draft of the interface layout for the system that will be developed [20]. The following are some interface designs for the system that will be built..

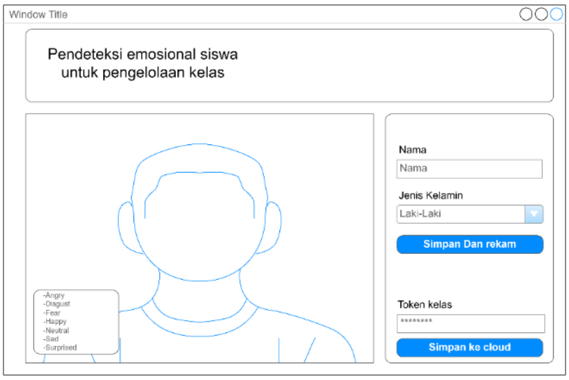

Figure 5. Detector Interface Design

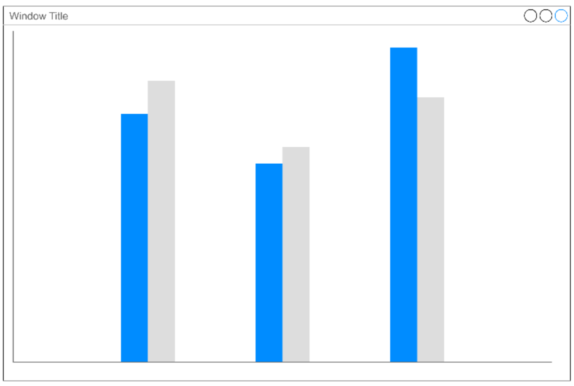

Figure 6. Graphical interface design of the detector

3.3. CNN Model Design

In the design of this model, we employ a Convolutional Neural Network (CNN) to measure students' concentration levels through facial image analysis. A crucial aspect of implementing CNN is the preparation and processing of data. The image data is prepared for training and validation using a data generator, and data augmentation is performed to enhance the model's performance.

The data that has been collected and processed will be augmented to create a data generator for training purposes by performing rescaling, which involves changing the pixel values from 0-255 to 0-1. The data is then resized to an image dimension of 48x48 pixels, and the color mode of the image is set to grayscale (black and white). This step is crucial to ensure that the model can learn more effectively.

By using this approach, we can efficiently prepare image data for training and validating the CNN model [21]. The data augmentation process, such as rescaling, helps the model to learn more effectively from image data by providing a uniform pixel value range [22]. This also enables the model to better generalize to new, unseen data before.

The model for training machines with convolutional neural networks (CNN) uses four convolutional layers.

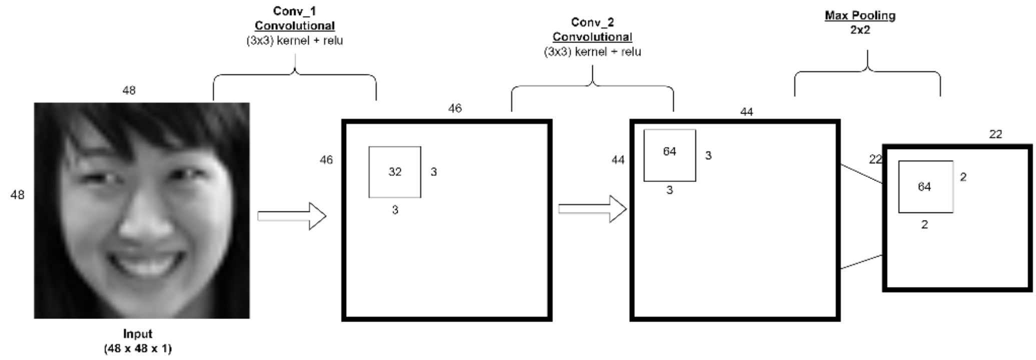

Figure 7. First layer CNN training

In this first layer, the input consists of an image with a size of 48x48 pixels and 1 grayscale channel. The initial convolution process is performed to extract features from the image using 32 filters with a 3x3 kernel and a ReLU activation function. This is followed by a second convolution process, which also extracts features from the image, but with 64 filters and a 3x3 kernel, again using the ReLU activation function. Afterward, a pooling process is applied to reduce the image size, utilizing 2x2 max pooling, which decreases the image size by 50%. The output of this layer is an image with a size of 22x22 pixels. Additionally, a Dropout layer is employed to prevent overfitting.

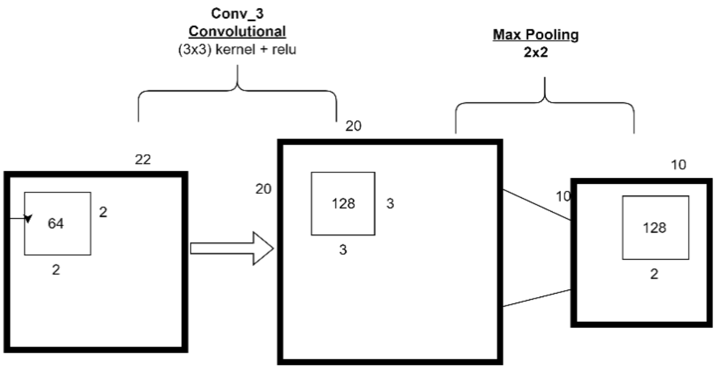

Figure 8. Second layer CNN Training

In the next layer, the input consists of an image with a size of 22x22 pixels. A convolution process is performed to extract features from the image using 128 filters and a 3x3 kernel, along with a ReLU activation function. As in the previous pooling process, this layer utilizes 2x2 max pooling to reduce the image size.

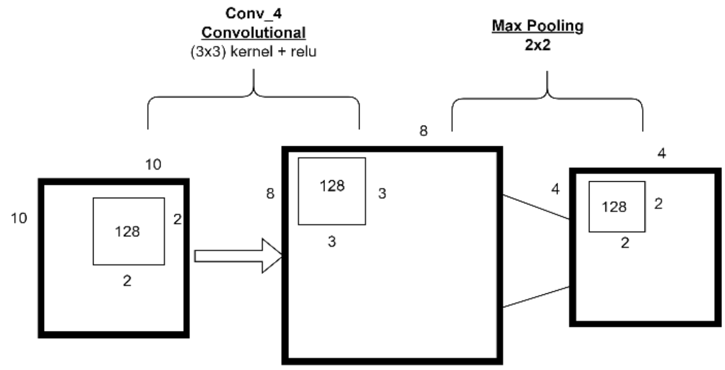

Figure 9. Third layer CNN training

In the subsequent layer, the input consists of an image with a size of 10x10 pixels. A convolution process is performed to extract features from the image using 128 filters with a 3x3 kernel and a ReLU activation function. Similar to the previous pooling process, this layer also employs 2x2 max pooling to reduce the image size.

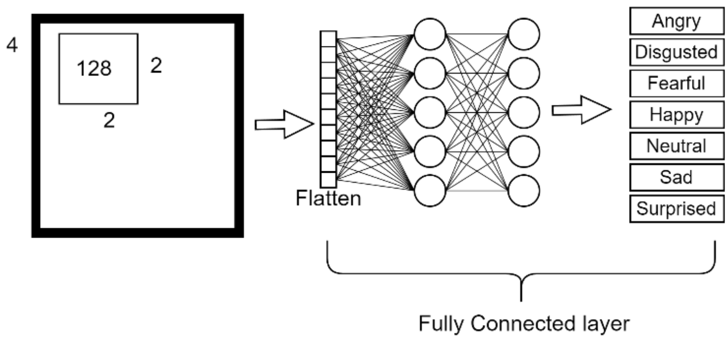

Figure 10. Fourth layer CNN training

Subsequently, all parameters are transformed into a one-dimensional vector (flattened) to be fed into the fully connected layer. In the dense layer, the output is reduced to 1024 units. Finally, in the last layer, classification is performed using the softmax function, which generates a set of probabilities corresponding to the classes in the dataset.

In the fully connected layer, features are integrated, and probabilities are calculated corresponding to the seven emotion classes. Finally, expression recognition is performed using the softmax function. The cross-entropy loss is computed to facilitate the training and evaluation of the model. The softmax and cross-entropy functions are defined by the equations below:

$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}}$$

$$L = -\sum_i^C t_i \log\left(f(s)_i\right)$$

Here, **C** represents the number of neurons in the fully connected layer, sj represents the value of each individual neuron, and si denotes the value obtained for the i-th class.

Subsequently, if we perform a summary on the constructed model, the data obtained will be as follows:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 46, 46, 32)        320

 conv2d_1 (Conv2D)           (None, 44, 44, 64)        18496

 max_pooling2d (MaxPooling2D  (None, 22, 22, 64)       0
 )

 dropout (Dropout)           (None, 22, 22, 64)        0

 conv2d_2 (Conv2D)           (None, 20, 20, 128)       73856

 max_pooling2d_1 (MaxPooling  (None, 10, 10, 128)      0
 2D)

 conv2d_3 (Conv2D)           (None, 8, 8, 128)         147584

 max_pooling2d_2 (MaxPooling  (None, 4, 4, 128)        0
 2D)

 dropout_1 (Dropout)         (None, 4, 4, 128)         0

 flatten (Flatten)           (None, 2048)              0

 dense (Dense)               (None, 1024)              2098176

 dropout_2 (Dropout)         (None, 1024)              0

 dense_1 (Dense)             (None, 7)                 7175

=================================================================
Total params: 2,345,607
Trainable params: 2,345,607
Non-trainable params: 0
_________________________________________________________________
```

Figure 11. Summary of the training model

3.4. Evaluation Model

After the modeling phase, the model was evaluated to measure its accuracy and loss using the Adam optimizer with 100 epochs of iteration. The evaluation results yielded the following validation accuracy:

```
Epoch 100/100
448/448 [==============================] - 14s 32ms/step - loss: 0.1428 - accuracy: 0.9495 - val_loss: 1.5775 - val_accuracy: 0.6275
```

Figure 12. Training Machine Evaluation Results

Based on the model's accuracy results, it was found that the loss was 14.28% with a relatively high accuracy of 94.95%. However, for the validation data, the loss value was also quite high at 157%, with an accuracy of 62.75%. This indicates that the model's accuracy on the validation data is 62.75%. The following section will present the accuracy and loss graphs for both the training and validation phases of the model:

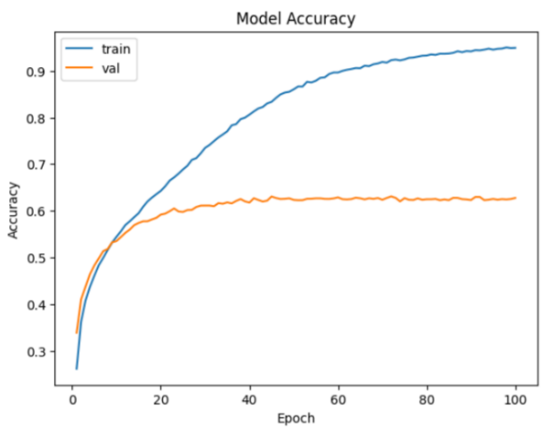

Figure 12. Model Accuracy Level graph

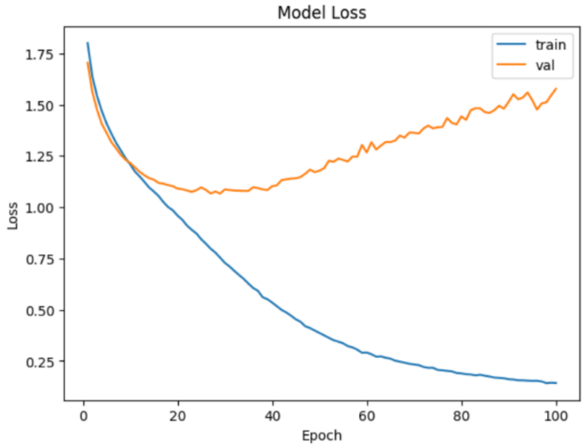

Figure 13. Loss Model Level graph

When a model exhibits high accuracy on training data but is accompanied by high loss values and lower accuracy on validation data, this can provide significant insights for researchers to better understand how the model interacts with the data. This situation suggests that the model has a strong potential to recognize complex patterns, further adjustments may be necessary. Consequently, even though the accuracy of the training data is high, the high loss value on the validation data indicates that in the context of multiclass classification or many classes, which are 7 classes, the accuracy can still be considered good. It also shows that the system is already fairly adept at detecting student emotions through facial expressions. However, the model requires further refinement.

3.5. Testing

After the coding process was completed and the CNN model was prepared, the next step was to test the system. To evaluate the accuracy of the model that has been developed, testing was conducted using the training model with the provided images.

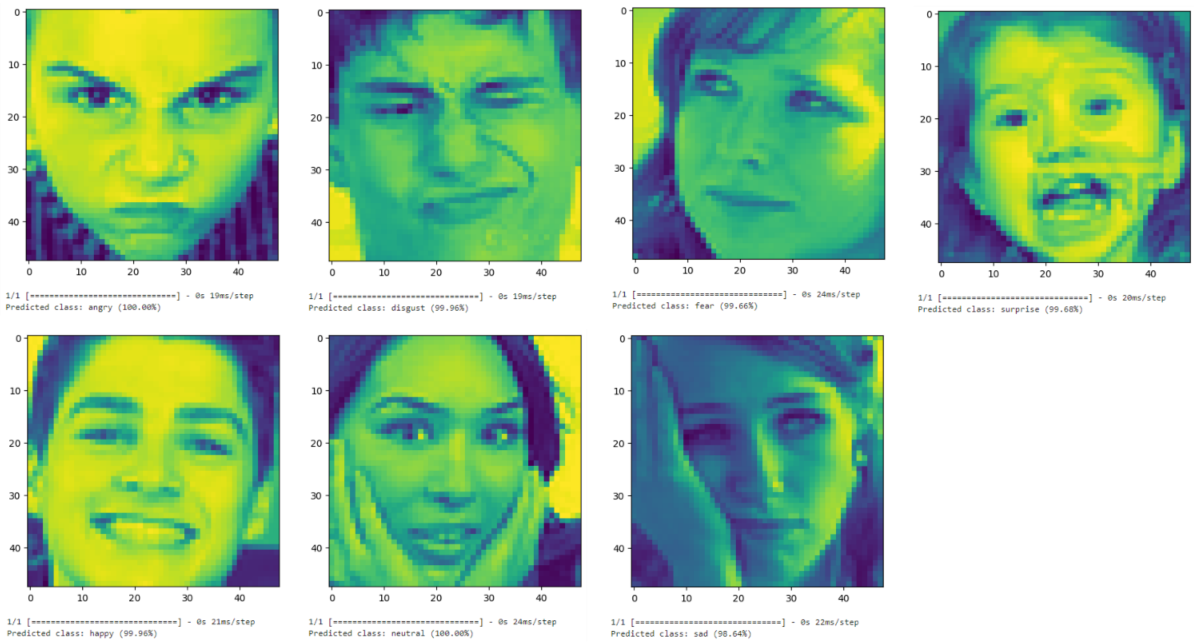

Figure 14. Testing Model with Training Images

The image above displays the results of testing the Convolutional Neural Network (CNN) model using previously trained images. Each sub-image presents a different facial expression, which has been predicted by the CNN model according to the relevant emotion class.

The prediction results include several emotion classes such as "angry," "disgust," "fear," "happy," "neutral," "sad," and "surprise." The percentages displayed beneath each image indicate the model's confidence level in determining the respective class, with all predictions showing a very high confidence level, reaching nearly 100%.

This testing aims to evaluate the performance of the CNN model in recognizing and classifying facial expressions based on the existing training data. With high prediction accuracy, the model demonstrates its ability to accurately identify various emotions, which indicates effective generalization of the model to the training data used.

The testing was also conducted in real-time over 2 x 40 minute sessions with a sample from Class X at SMAN 5 Bukittinggi during an Informatics lesson. The purpose of this testing was to evaluate the emotional levels of students during the learning process by using the trained model to classify various facial expressions, as follows:

Figure 15. Live testing documentation

From the testing carried out directly in the class, the average value in the form of a graph of students' emotions was obtained, as shown in Figure 16 below.

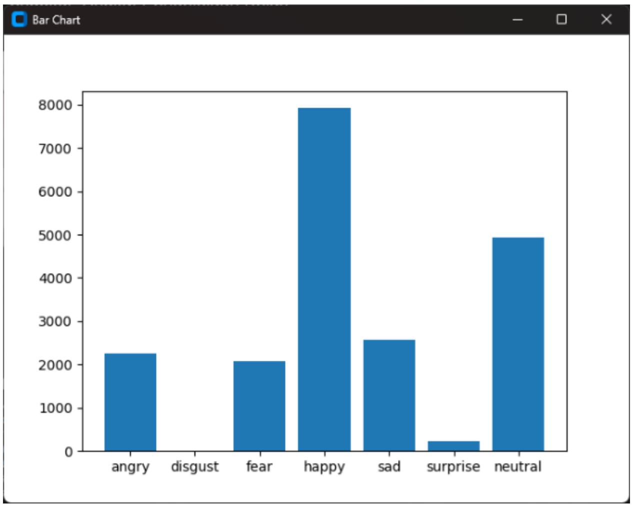

Figure 16. Results of the average emotional score of students in class

The results of this testing reveal the emotional distribution of students based on the emotion classes detected by the CNN model. The identified emotion classes include "angry," "disgust," "fear," "happy," "sad," "surprise," and "neutral." In the bar graph, it is evident that the emotion "happy" has the highest frequency, followed by "neutral," while the emotion "surprise" has the lowest frequency.

Overall, the results indicate that the majority of students exhibited happy and neutral emotions during the learning process, which may suggest a positive classroom atmosphere and active student participation. Conversely, negative emotions such as anger, disgust, and sadness were less frequent, indicating that only a small proportion of students may have felt uncomfortable or less motivated during the lesson. This testing provides valuable insights for educators in assessing students' emotional conditions and can be utilized to enhance teaching quality in the future.

3.6. Deployment

This phase includes the implementation of the software to the client, necessary improvements, performance evaluation of the software, and development based on feedback to ensure that the system can operate and evolve according to its objectives and requirements. Additionally, this process involves user training to ensure they can effectively utilize the software and support the system's long-term sustainability [23].

After the system was deployed and tested with students by the teacher, there were several comments from the teacher regarding the developed product. Buk Sri Astuti Rahmah, S.Pd, commented: "The product is very engaging for use in teaching and can serve as material/data for teachers in classroom management."

4. Conclusion

Through the use of cameras in the classroom, students are recorded in real-time, generating visual data that is then processed by the system to focus on facial areas. This facial data is processed by a Convolutional Neural Network (CNN) capable of identifying students' emotional expressions in real time. This information provides valuable insights for teachers regarding students' emotional responses to the lesson content or interactions in the classroom. With a deeper understanding of students' emotions, teachers can design more targeted teaching approaches and provide more effective support.

The implementation of CNN in this system involves several critical stages, including model training using a dataset containing images of students' faces along with corresponding emotional labels, as well as data preprocessing and model creation. The results from machine training show a high accuracy of 94.95% on the training data. However, performance on validation data presents challenges with a relatively high loss value of 157% and an accuracy of 62.75%. Although this accuracy can still be considered good for classification with seven different classes, these results indicate that the model needs further adjustment to improve generalization and performance on unseen data.

Direct testing in Class X at SMAN 5 Bukittinggi demonstrated that the CNN model was able to identify students' emotional conditions during the learning process with fairly high accuracy. The majority of students exhibited happy and neutral emotions, indicating a conducive and positive classroom atmosphere. Conversely, negative emotions appeared with lower frequency, suggesting that only a small proportion of students may have been less engaged or experienced difficulties in following the lesson.

The CNN-based emotion detection system makes a significant contribution to the field of education, particularly in enhancing the quality of teaching through a more adaptive and responsive approach to students' needs. With this tool, educators can gain a deeper understanding and adjust their teaching methods to create a more effective and inclusive learning environment. This research also opens opportunities for further development, such as improving model accuracy and expanding the system's application to various other educational contexts.

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