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Implementation of Handwritten Digit Recognition Using CNN in an Augmented Reality-Based Geometry Learning Application

Azizah Fauni Saputri[1] and Feri Candra[2]
[1,2]Informatics Department, University of Riau, Pekanbaru, Riau, Indonesia
e-mail: azizah.fauni2594@student.unri.ac.id[1], feri@eng.unri.ac.id[2]
*Correspondence: *feri@eng.unri.ac.id*

Abstract: *Instruction on 3D shapes in elementary schools is still dominated by the use of two-dimensional media, making it difficult for students to visualize three-dimensional objects. Furthermore, most Augmented Reality (AR)-based learning applications focus primarily on presenting learning materials without providing an assessment mechanism that supports handwritten student answers. This study aims to implement Handwritten Digit Recognition (HDR) based on a Convolutional Neural Network (CNN) in an AR-based 3D shape learning application. The proposed approach integrates CNN-based handwritten digit recognition as an evaluation mechanism within the AR-based learning application, allowing students' handwritten answers to be automatically recognized and evaluated. The CNN model utilizes the LeNet-5 architecture and was trained using a combined dataset consisting of 70,000 MNIST images and 10,000 handwritten images independently collected by the researcher. The testing results show that the model achieved an accuracy of 98.32%, while HDR testing within the application using 250 samples of student handwriting achieved an accuracy of 96.80%. The results indicate that the implementation of CNN-based HDR in an AR-based 3D shape learning application can recognize handwritten digits with high accuracy and provide an automated learning evaluation mechanism based on handwritten answers.*

Keywords: *CNN, Handwritten Digit Recognition, LeNet-5, Augmented Reality.*

1. Introduction

Advances in information technology have driven the use of digital learning media in the educational process. Augmented Reality (AR) is one of the technologies increasingly applied in education because it enables virtual three-dimensional objects to be presented within the user's surrounding environment in real time [1][2]. In mathematics instruction, specifically regarding the topic of 3D shapes, the use of AR has been shown to enhance visualization skills, conceptual understanding, and student engagement in the learning process [3][4]. Observations and interviews with the mathematics teacher at SD Negeri 006 Muda Setia, Bandar Sei Kijang District, Pelalawan Regency, Riau Province, indicate that instruction on 3D shapes is still conducted using conventional methods, relying on textbooks, the whiteboard, and written exercises. The teacher reported that students still struggle to visualize three-dimensional shapes, distinguish their components, and solve problems related to surface area and volume. This situation highlights the need for instructional media capable of presenting visualizations of three-dimensional objects while simultaneously supporting the digital assessment of learning.

One technology that can support this need is Handwritten Digit Recognition (HDR), a technology for automatically recognizing handwritten digits [5]. Handwriting offers advantages over typing, particularly in supporting the learning process [6]. Convolutional Neural Networks (CNNs) are widely used for handwritten digit recognition because they are capable of automatically extracting relevant features from images [7][8]. Research by Tanjung et al. shows that CNNs are capable of achieving an accuracy of approximately 99% on the MNIST dataset [9]. Research by Winanto et al. also demonstrates that CNNs exhibit high performance in handwritten digit recognition across various data variations [10]. In addition, Lubis and Susilawati achieved an accuracy of 99.49% using the DenseNet-201 CNN architecture [11].

The results demonstrate that the CNN possesses excellent capabilities in handwritten digit recognition [9][10][11]. Nevertheless, previous studies on handwritten digit recognition primarily focus on the development and evaluation of recognition models [9][10][11]. Meanwhile, research on AR-based learning media has utilized Augmented Reality to support the visualization of three-dimensional learning objects, including 3D shapes[1][12] . However, these approaches are generally developed separately, where CNN-based HDR focuses on digit classification while AR-based learning applications focus on the visualization and presentation of learning materials. This indicates an opportunity to integrate handwritten digit recognition as an evaluation mechanism within an AR-based learning application.

Based on this research gap, the novelty of this study lies in the integration of CNN-based HDR into an Augmented Reality-based learning application for 3D shapes, with HDR serving as a mechanism for evaluating students' answers through handwriting. The developed application can help students learn 3D shapes through the visualization of three-dimensional objects using AR and answer quiz questions by directly writing digits on the canvas. The resulting handwritten images are then processed and automatically classified using a CNN model based on the LeNet-5 architecture. The model was trained using a combined dataset of 80,000 images, consisting of 70,000 MNIST images and 10,000 handwritten images independently collected by the researcher. The model was subsequently integrated into the application to recognize students' handwritten answers during the quiz. Thus, this study integrates AR-based 3D shape visualization with a handwriting-based evaluation mechanism using CNN-based HDR within a single learning application.

2. Methods

This study employs an experimental method to develop an Augmented Reality (AR)-based learning application for 3D shapes that integrates Handwritten Digit Recognition (HDR) based on a CNN. The application was developed using the Multimedia Development Life Cycle (MDLC) method, while the HDR model was built using the LeNet-5 architecture. Broadly, the research encompasses problem identification, application development, CNN model construction, model implementation within the application, and system evaluation. The research workflow is illustrated in Figure 1.

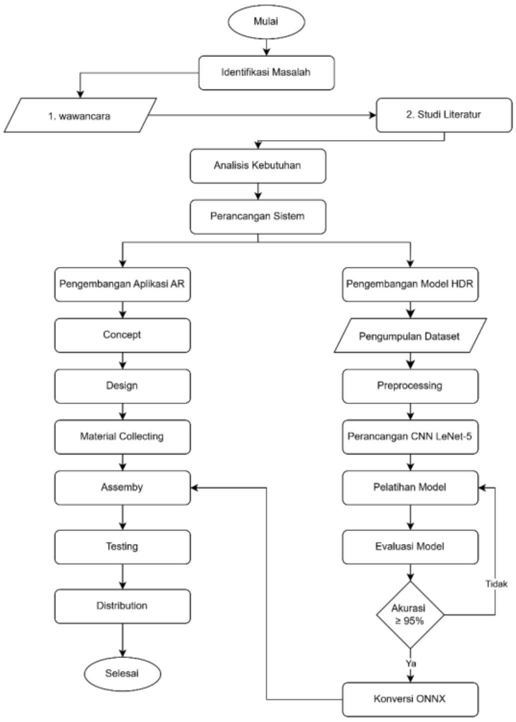

Figure 1. Research Stages

A. Multimedia Development Life Cycle (MDLC)

The development of an Augmented Reality-based application for learning 3D shapes utilizes the Multimedia Development Life Cycle (MDLC) method, which comprises six stages: concept, design, material collecting, assembly, testing, and distribution [12]. This method was selected because it provides a systematic multimedia development workflow, spanning from the planning phase to the point where the application is ready for use. The MDLC stages involved in this study are illustrated in Figure 2.

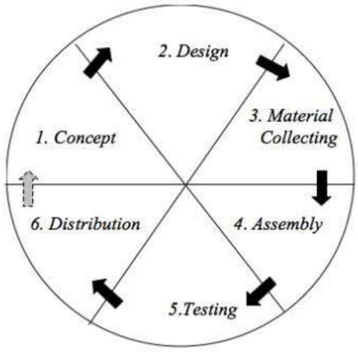

Figure 2. MDLC Development Stages

1. Concept
   This stage is conducted to identify system requirements through observation and interviews with the Mathematics teacher at SD Negeri 006 Muda Setia, Bandar Sei Kijang District, Pelalawan Regency, Riau Province. The results of this stage serve as the basis for determining the application's objectives, learning materials, and the features to be developed.
2. Design
   The design phase encompasses the design of the user interface, application navigation flow, and Augmented Reality markers, as well as the design of learning features and quizzes.
3. Material Collecting
   This stage involves gathering all application requirements, including 3D geometric models, AR markers, learning materials, interface images, as well as the MNIST and handwriting datasets used for training the CNN model.
4. Assembly
   At this stage, the application is developed using Unity and the Vuforia Engine. All multimedia assets are integrated with a CNN model, enabling the application to display three-dimensional objects and recognize handwritten digits within the quiz feature.
5. Testing
   The testing phase was conducted to evaluate the performance of the application and the CNN model through model testing, HDR testing within the application, functional testing, System Usability Scale (SUS) testing, and content validation by teachers.
6. Distribution
   The distribution phase involves packaging the application into an Android installer format (APK) so that it can be installed and used directly on user devices.

B. CNN Model Development

The HDR model was built using the LeNet-5 architecture, a CNN architecture developed for handwritten character recognition that is widely used for digit classification [13]. The LeNet-5 architecture consists of two convolutional layers, two average pooling layers, one flatten layer, two fully connected layers, and one output layer using the Softmax activation function. The model architecture is shown in Table 1.

Table 1. LeNet-5 CNN Model Architecture

Layer	Parameter	Output
Input	32×32×1	32×32×1
Conv2D	6 filters, 5×5, padding='same', tanh	32×32×6
AveragePooling2D	2×2	16×16×6
Conv2D	16 filters, 5×5, tanh	12×12×16
AveragePooling2D	2×2	6×6×16
Flatten	–	576
Dense	120 neurons, tanh	120
Dense	84 neurons, tanh	84
Output	10 neurons, Softmax	10

The dataset used in this study consisted of a combined collection of 80,000 images, comprising 70,000 MNIST images and 10,000 handwritten images independently collected by the researcher. Prior to training, all images underwent a preprocessing stage to standardize the input data and preserve essential image information [14]. The preprocessing steps included converting the images to grayscale with a size of 32 × 32 pixels and normalizing pixel values from the range 0–255 to 0–1. Subsequently, the combined dataset was randomly shuffled and divided using a stratified split into 70% training data (56,000 images), 15% validation data (12,000 images), and 15% testing data (12,000 images). The stratified split was used to maintain the proportion of each digit class from 0 to 9 across the training, validation, and testing sets, ensuring that the MNIST and researcher-collected handwritten data were proportionally distributed across all three subsets. After the dataset was split, the labels in each subset were converted into one-hot encoding format for use in the model training process.

Model training was performed using the Adam optimizer with a learning rate of 0.001, a batch size of 128, and a maximum of 30 epochs. The Adam optimizer was chosen because it is capable of adaptively adjusting the learning rate, making it widely used in deep neural network training [15]. To obtain the best model while minimizing the risk of overfitting, an Early Stopping mechanism with a patience value of 5 was implemented, along with ModelCheckpoint to save the model based on the best validation accuracy. The model training parameters are presented in Table 2.

Table 2. CNN Model Training Parameters

Parameter	Value
Optimizer	Adam
Learning rate	0,001
Batch Size	128
Maximum Epochs	30
Loss Function	Categorical crossentropy
Metric	Accuracy
Early Stopping	monitor val_loss, patience 5, restore best weights

C. Application Development

The GeoSpace application was developed using Unity as the development platform and the Vuforia Engine as the Software Development Kit (SDK) to implement AR features. In the marker-based AR implementation, the marker serves as a reference point detected by the device's camera to display a three-dimensional virtual object in real-time [16]. The application presents material on 3D shapes including cubes, rectangular prisms, prisms, pyramids, cylinders, cones, and spheres along with information on their components, surface area, and volume to support the learning process.

Serving as a tool for evaluating learning, the application provides a quiz feature where students write numerical answers on a canvas area. The handwritten images undergo preprocessing steps identical to those used during model training; they are then classified using a CNN model that has been converted to the ONNX format and integrated into Unity via Sentis. The prediction results are compared against the correct answers and displayed to the user as feedback.

D. Evaluation

An evaluation was conducted on the CNN model and the developed application. The model's performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix metrics, with precision, recall, and F1-score serving to measure the model's classification capability [17]. After the model was implemented into the application, HDR testing was conducted using 250 samples of student handwriting that had not been used during the model's training or testing phases. Additionally, functional testing, System Usability Scale (SUS) testing involving 30 students, and content validation by three mathematics teachers were carried out.

3. Results and Discussion

A. Application Development Results

The GeoSpace application was successfully developed using Unity and Vuforia Engine in accordance with the system design. It provides an Augmented Reality-based learning feature for 3D geometric shapes, capable of displaying three-dimensional objects based on markers detected by the device's camera. The content covers cubes, rectangular prisms, prisms, pyramids, cylinders, cones, and spheres, accompanied by information on their geometric properties, surface area, and volume.

In addition to 3D object visualization, the application includes a quiz feature to serve as a tool for evaluating learning. Within this feature, students can write their answers as digits on a canvas area. The resulting handwriting is processed using a CNN-based Handwritten Digit Recognition model, enabling the system to automatically recognize the digits and display the evaluation results to the user. Implementation results demonstrate the successful integration of all key features—specifically AR-based 3D shape visualization and the HDR-based quiz into a single application. The application interface is shown in Figure 3.

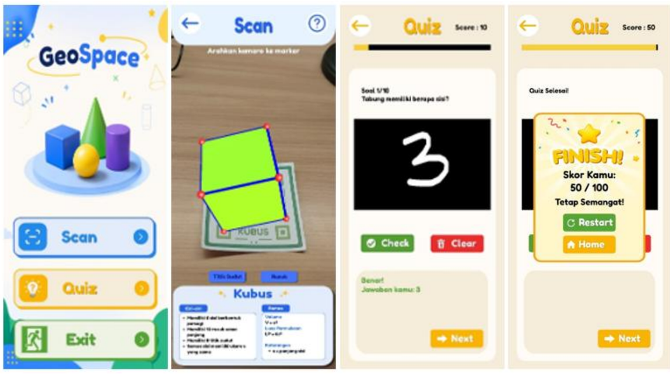

Figure 3. Application Interface

B. CNN Training Results

The handwritten digit recognition model was built using the LeNet-5 architecture and trained on a combined dataset of 80,000 images, comprising 70,000 MNIST images and 10,000 handwritten images collected by the researchers. The training process yielded the best model at the 8th epoch, while the early stopping mechanism halted training at the 13th epoch because there was no decrease in validation loss for five consecutive epochs.

The training results show a training accuracy of 99.47% and a validation accuracy of 98.27%, with a training loss of 0.0203 and a validation loss of 0.0623. The relatively small difference between the training and validation values indicates that the model possesses good generalization capabilities without overfitting. The best model was obtained at the 8th epoch; consequently, the model weights from that epoch were used for the testing and application implementation phases. Graphs illustrating the progression of accuracy and loss during the training process are presented in Figure 4.

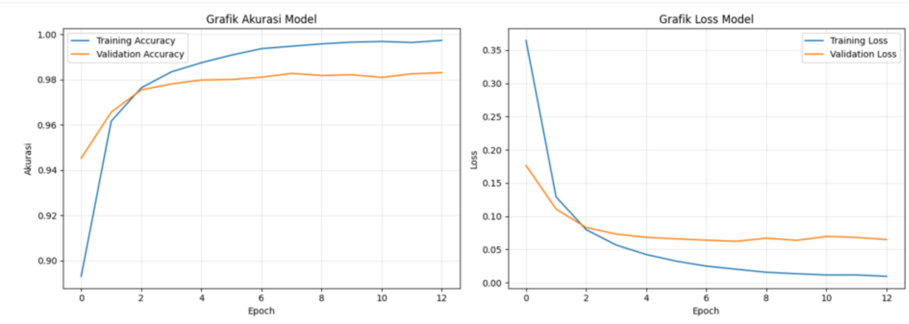

Figure 4. Training Accuracy and Loss Curves

C. CNN Testing Results

After the training process was completed, the best model was evaluated using test data that had not been used during the training or validation phases. The test results showed that the model achieved an accuracy of 98.32%, with precision, recall, and F1-score each at 98.32%. Evaluation using a confusion matrix indicates that the majority of digits were correctly classified. Misclassifications were still observed among digits with similar shapes, particularly 3, 5, 7, and 9 but the number of such errors was relatively small and did not significantly impact the model's overall performance.

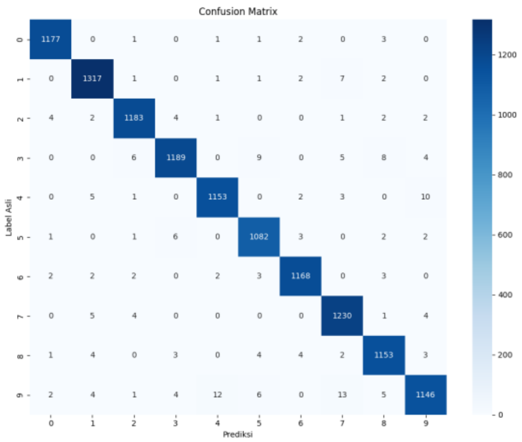

Figure 5. Confusion Matrix

D. Application Evaluation

1. HDR Testing Results

After the CNN model was implemented in the GeoSpace application, HDR testing was conducted using 250 samples of student handwriting that had not been used during the model's training or testing phases. This testing aimed to evaluate the model's ability to recognize handwritten digits under real-world usage conditions within the application.

Figure 6 shows an example of HDR test results on students' handwriting. Most digits were correctly recognized by the model, whereas some were misclassified due to variations in handwriting shapes that share similar visual characteristics.

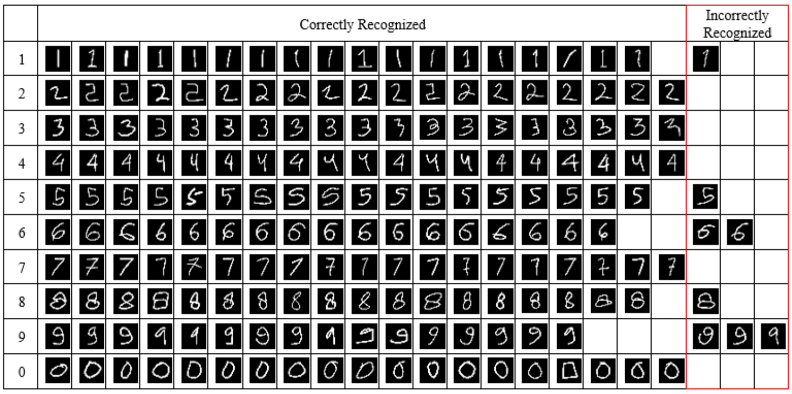

Figure 6. HDR Testing Results on Handwritten Digits

Furthermore, the overall HDR test results are presented in the table 3

Table 3. HDR Testing Results on Handwritten Digits

Digit	Number of Tests	Correctly Recognized	Incorrectly Recognized	Accuracy (%)
1	25	24	1	96,00%
2	25	25	0	100,00%
3	25	25	0	100,00%
4	25	25	0	100,00%
5	25	24	1	96,00%
6	25	23	2	92,00%
7	25	25	0	100,00%
8	25	24	1	96,00%
9	25	22	3	88,00%
0	25	25	0	100%
Total	250	242	8	96,80%

Based on Table 3, out of 250 tested handwriting samples, the model correctly recognized 242 digits and misclassified 8, resulting in an accuracy rate of 96.80%. Digits 0, 2, 3, 4, and 7 were recognized with 100% accuracy, whereas digit 9 achieved the lowest accuracy at 88%. These results demonstrate that the model is capable of effectively recognizing the majority of students' handwriting, despite variations in writing styles among users.

2) Functional Testing Results

Functional testing was conducted to ensure that all features of the GeoSpace application operate according to the system design. The testing covered marker scanning, 3D geometric object visualization, presentation of learning materials, quiz administration, and handwritten digit recognition using a CNN model. The functional testing outcomes are presented in Table 4.

Table 4. Application Functional Testing Results

No.	Feature	Test Scenario	Test Result	Status
1	Home Page	Launch the application	The home page is displayed successfully.	Passed
2	Scan Page	Tap the Scan button	The AR camera is displayed successfully.	Passed
3	Marker Detection	Point the camera at the marker	The marker is recognized successfully.	Passed

4	3D Object	Marker is recognized	The 3D object is displayed successfully.	Passed
5	Geometry Information	The 3D object is displayed	The object name, faces, edges, vertices, surface area formula, and volume formula are displayed successfully.	Passed
6	Edges Button	Tap the Edges button	The edge visualization is displayed successfully.	Passed
7	Vertices Button	Tap the Vertices button	The vertex visualization is displayed successfully.	Passed
8	Rotation and Zoom	Drag or pinch the object	The object can be rotated and zoomed successfully.	Passed
9	Quiz Page	Tap the Quiz button	The quiz page is displayed successfully.	Passed
10	Handwriting Canvas	Write a digit on the canvas	The canvas successfully accepts handwritten input.	Passed
11	CNN Prediction	Tap the Submit button	The prediction result is displayed successfully.	Passed
12	Quiz Score	Complete all quiz questions	The result and score page is displayed successfully.	Passed

Based on Table 4, all application functions were successfully executed in accordance with system requirements, with no functional errors detected. These results indicate that integrating the CNN model into the GeoSpace application did not affect its core functionality, allowing all features to operate as intended.

3) Usability Testing and Material Validation

Usability testing using the System Usability Scale (SUS) instrument yielded an average score of 88, placing it in the "Excellent" category. Furthermore, content validation conducted by three mathematics teachers resulted in a 100% feasibility rating. These results demonstrate that the GeoSpace application not only performs well technically but is also user-friendly and presents learning materials that align with the educational needs of elementary schools.

E. Discussion

The research results demonstrate that the integration of HDR based on CNN into an AR application for 3D shape learning was successfully implemented. Unlike previous studies that primarily focused on developing handwritten digit recognition models or utilizing AR as a visualization medium, this study combines both technologies within a single learning application. This integration provides three-dimensional shape visualization while also supporting learning assessment through handwritten answers.

The CNN model using the LeNet-5 architecture achieved a testing accuracy of 98.32%. This result demonstrates that LeNet-5 can provide high performance in handwritten digit recognition despite its relatively simple architecture. This finding is consistent with studies by Tanjung et al. [9] , Winanto et al. [10], and Lubis and Susilawati [11], which demonstrated the high classification capability of CNNs for handwritten digit recognition. However, these results should be interpreted by considering the differences in datasets, architectures, and experimental settings used in each study. For example, Lubis and Susilawati [9] employed the DenseNet-201 architecture, whereas this study used LeNet-5. Therefore, the accuracy of 98.32% indicates that LeNet-5 was still able to achieve strong recognition performance under the experimental conditions of this study.

As a baseline comparison, the same LeNet-5 architecture was trained using 70,000 MNIST images only without additional handwritten images. The MNIST-only model achieved a testing accuracy of 98.20%, while the model trained using the combined dataset of 80,000 images, consisting of MNIST data and 10,000 handwritten images collected by the researcher, achieved an accuracy of 98.32%. The difference of 0.12 percentage points indicates a slight improvement in testing accuracy after the addition of the 10,000 handwritten images. Although the improvement was relatively small, the additional images provided greater variation in handwriting characteristics, including differences in shape, size, stroke thickness, and writing patterns. The combined-dataset model maintained a high testing accuracy of 98.32%, indicating strong handwritten digit recognition performance.

Based on the testing results using 250 student handwriting samples, 242 samples were successfully recognized and 8 samples were incorrectly recognized, resulting in an accuracy of 96.80%. Digits 0, 2, 3, 4, and 7 were correctly recognized with an accuracy of 100%, while misclassifications occurred for digits 1, 5, 6, 8, and 9. The misclassifications included digit 1 being recognized as 7, digit 5 as 6, digit 6 as 5, digit 8 as 0, and digit 9 as 0 and 4. These errors may be influenced by similarities in the shape and stroke patterns of certain digits. In addition, differences in students' handwriting characteristics, such as stroke shape, size, thickness, inclination, and curvature, may produce digit forms that differ from the patterns learned by the model. This indicates that variations in handwriting under real-world usage conditions remain one of the factors that can affect HDR classification performance.

Compared with the model testing results, the application-level accuracy of 96.80% was lower than the model testing accuracy of 98.32%, with a difference of 1.52 percentage points. This difference may be associated with the greater variation in students' handwriting compared with the data used during model development. In addition, the way students wrote digits on the application canvas may affect the characteristics of the images received by the model. Nevertheless, the application-level accuracy of 96.80% remained above the research target of 95%, indicating that the model achieved the performance target established in this study.

In addition to HDR performance, functional testing showed that all application features operated according to the designed requirements without functional errors. Usability testing using the System Usability Scale (SUS) obtained a score of 88, categorized as Excellent, while content validation conducted by three mathematics teachers obtained a feasibility rating of 100%. These results indicate that the GeoSpace application was able to perform the designed functions and received good usability and content feasibility evaluations. This study has several limitations. The developed HDR model is limited to recognizing digits from 0 to 9. In addition, the 10,000 additional handwritten images were independently collected by the researcher and may not fully represent the diversity of handwriting styles. Application-level HDR testing was also limited to 250 student handwriting samples. These limitations indicate the need for a larger and more diverse dataset and a greater number of users in future research.

Overall, the results demonstrate that the integration of AR-based 3D shape visualization and CNN-based HDR can be implemented within a single learning application. AR provides visualization of three-dimensional shape objects, while CNN performs handwritten digit recognition. This integration provides a handwriting-based evaluation mechanism, allowing digit answers written in the application to be automatically recognized by the system.

4. Conclusions

This study successfully implemented HDR based on CNN using the LeNet-5 architecture in an AR-based 3D shape learning application. The CNN model was trained using a combined dataset of 80,000 images and achieved a testing accuracy of 98.32%. Furthermore, application-level HDR testing using 250 handwritten digit samples from students achieved an accuracy of 96.80%. In addition to its classification performance, the GeoSpace application demonstrated satisfactory evaluation results. All application features functioned as intended, the usability evaluation achieved a SUS score of 88, categorized as Excellent, and the content validation obtained a feasibility rating of 100%.

The main contribution of this study is the integration of CNN-based HDR as a handwriting-based answer evaluation mechanism into an AR-based 3D shape learning application. This integration combines three-dimensional shape visualization with automatic recognition of handwritten answers within a single learning application. However, this study has several limitations. The HDR model is limited to recognizing digits from 0 to 9. The 10,000 additional handwritten images used for model development were independently collected by the researcher and may not fully represent the diversity of handwriting styles. In addition, application-level HDR testing was conducted using 250 student handwriting samples. Future research can expand the dataset with more diverse handwriting styles and a larger number of users, as well as extend the recognition capability to mathematical symbols and more complex handwritten answers.

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