ISSN 2355-0082

Approach Convolutional Neural Network LeNet-5 for Interactive Learning of Korean Syllables (Hangul)

Vasyilla Kautsar Al Fitra Yudha[1], Arvita Agus Kurniasari[2],
Aji Seto Arifianto[3], Faisal Lutfi Afriansyah[4]
Departement of Informatics Technology, State Polytechnic of Jember, Jember, Indonesia
[1]vasyillakafy@gmail.com, [2]arvita@polije.ac.id, [3]ajiseto@polije.ac.id, [4]faisal.lutfi@polije.ac.id

Accepted 2 July 2024
Approved 19 November 2024

***Abstract*— The increasing popularity of South Korean culture among Indonesian society has led to a growing interest in gaining a deeper understanding of the country, including a desire to master the Korean language. However, learning the Korean alphabet (hangul) often presents challenges due to its characters being unfamiliar to the Indonesian people. Therefore, engaging and interactive learning media are needed to assist in the learning process. Within this endeavor, a learning website called Learn Hangul was developed, focusing on two main features: learning hangul characters and their arrangement, as well as practicing writing syllables using Korean letters. This website was developed using the Convolutional Neural Network (CNN) LeNet-5 to facilitate learning, with black box testing results indicating good functionality. Model performance evaluation yielded satisfactory values, with model accuracy at 89.2%, precision at 89.7%, recall at 88.8%, and an F1-score of 89.2%. Direct testing with users also showed a high success rate, with 80% of respondents experiencing an increase in their knowledge of Korean characters (Hangul) after trying to learn them on the Learn Hangul website. Thus, the Learn Hangul website serves as a useful learning tool for those interested in studying the Korean alphabet (hangul).**

***Index Terms*— Convolutional Neural Network; LeNet-5; Korean Language; Hangul; Website; Learning Media**

I. Introduction

Hallyu (한류) is a Korean term where "Han" (한) refers to "Hankuk" meaning Korea, and "Lyu" (류) means wave or flow (Valenciana and Pudjibudojo, 2022). Hallyu refers to the growing public interest in Korean pop and traditional arts around the world. The influence of Hallyu has made Indonesia one of the Asian countries affected by the Korean Wave. With the regular consumption of Korean cultural content, this leads to a desire to learn the Korean language, fostering an interest in studying Korean [1].

Research by Mutiara shows a strong correlation between watching Korean dramas and the interest in learning the Korean language among students at Mercu Buana University's Faculty of Communication Sciences. Their study found that exposure to Korean dramas influences Korean language learning interest by 43.8% [2]. Another research by Hasanah, based on a survey of students in UGM's Korean Language D3 Program revealed that 92.6% were initially drawn to Korean culture before being motivated to learn the language. Moreover, 96.3% confirmed using Korean culture as a learning tool, underscoring its significant role in attracting students to study Korean [1].

Furthermore, Many fans of Korean entertainment are drawn to South Korea not only for its cultural appeal but also for its highly regarded education system, recognized globally for its excellence [3]. The availability of scholarships, including the KGSP (Korea Global Scholarship Program), offered by both local and Indonesian governments, further encourages students to pursue studies at prestigious South Korean universities. As of November 2019, approximately 1,500 Indonesian students were enrolled in universities across South Korea, as reported by the Embassy of the Republic of Indonesia in Seoul.

The impact of the popularity of Korean culture in Indonesia and the growing interest in studying in South Korea has led to an increased interest among Indonesians in learning the Korean language. This ranges from fans who want to know more about South Korea to students who may live alongside Korean society. Before learning the Korean language directly, students first need to familiarize themselves with the official script of South Korea, which is Hangul.

Hangul is the official name of the Korean alphabet used by the Korean people, created by the Great King Sejong. Hangul consists of 40 characters, including 21 vowels and 19 consonants (Seon Jung et al., 2015). Hangul is written differently from the usual alphabet, with each letter forming a specific character, and the characters are written in square blocks similar to Chinese characters, which is called Gulja [4].

According to the International Standard Curriculum of The Korean Language for level 1 in the writing field, there are several achievement standards that must be met. One of them is that students should be able to form words by combining consonant and vowel letters according to orthographic rules. To form words, syllables are needed as the building blocks. When writing syllables using Hangul, there are specific writing rules. The unfamiliarity of the character shapes and writing methods for Indonesians may present some difficulties at the beginning of the learning process.

Currently, there are many free platforms that provide learning materials for the Korean language, such as YouTube, websites, and even on social media like Instagram. However, the learning resources often focus only on reading and listening skills or theoretical learning without direct practice. Meanwhile, writing practice or direct application can hone skills and improve proficiency in writing Hangul, whose characters are unfamiliar to Indonesians. Therefore, engaging and interactive learning media are needed to achieve optimal learning outcomes.

Current technological advancements can be maximized to make the learning process easier and more flexible, by creating a "Learn Hangul" website for introducing the writing patterns of Hangul syllables. In addition to theoretical learning, students can also practice writing directly. This way, students will not only become proficient in reading but also be able to write and form Hangul syllables correctly.

Website development can be done using one of the methods from neural networks. Neural networks can be described as functioning similarly to the human brain, by training the system to recognize patterns in training data to achieve a good level of accuracy. In the process, each pixel is analyzed and matched with the training data that has undergone the neural network process, making it very suitable for solving classification or pattern recognition problems in objects [5]. Convolutional Neural Network (CNN) is a type of neural network commonly used to process image data. CNNs are typically employed to detect and recognize objects in images [6]. CNNs have a deep network architecture, allowing them to achieve high accuracy and produce good results [7].

Based on existing issues and previous research conducted on pattern recognition in objects, this study employs the Convolutional Neural Network (CNN) method to recognize the writing of Korean syllabic characters (Hangul).

II. LITERATURE REVIEW

A. Hangul

Hangul (한글) is the alphabet used by the Korean people for everyday, consists of 40 letters, comprising 21 vowel letters and 19 consonant letters. Among the 21 vowel letters, 10 are basic vowels and 11 are expanded vowels derived from the basic forms. As for the 19 consonant letters, 14 are basic consonants, and 5 more letters are double consonants [8].

B. Korean Syllables

Each Hangul letter must have a pair (consonant + vowel) to be pronounced and form a syllable, with each letter placed according to specific positional rules. To form a Hangul syllable, several patterns are used: CV, CVC, CVVC, CVCC, and CVVCC. C represents a consonant and V represents a vowel. The arrangement of Korean syllabic characters shown in Fig 1.

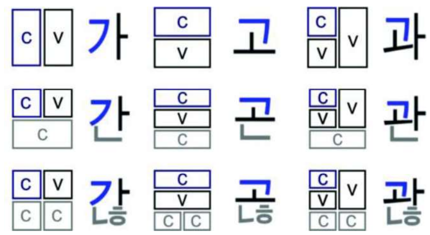

Fig 1. Arrangement of Korean syllables [9]

Vowel letters are arranged vertically or horizontally. ㅏ, ㅑ, ㅓ, ㅕ, ㅣ are vertical vowels, while ㅗ, ㅛ, ㅜ, ㅠ, ㅡ are horizontal vowels. When forming Hangul letters into syllables, consonants are written to the left of vertical vowels and above horizontal vowels [8]. The combination of one consonant with one vowel shown in Fig 2.

	ㅏ	ㅑ	ㅓ	ㅕ	ㅗ	ㅛ	ㅜ	ㅠ	ㅡ	ㅣ
ㄱ	가	갸	거	겨	고	교	구	규	그	기
ㄴ	나	냐	너	녀	노	뇨	누	뉴	느	니
ㄷ	다	댜	더	뎌	도	됴	두	듀	드	디
ㄹ	라	랴	러	려	로	료	루	류	르	리
ㅁ	마	먀	머	며	모	묘	무	뮤	므	미
ㅂ	바	뱌	버	벼	보	뵤	부	뷰	브	비
ㅅ	사	샤	서	셔	소	쇼	수	슈	스	시
ㅇ	아	야	어	여	오	요	우	유	으	이
ㅈ	자	쟈	저	져	조	죠	주	쥬	즈	지
ㅊ	차	챠	처	쳐	초	쵸	추	츄	츠	치
ㅋ	카	캬	커	켜	코	쿄	쿠	큐	크	키
ㅌ	타	탸	터	텨	토	툐	투	튜	트	티
ㅍ	파	퍄	퍼	펴	포	표	푸	퓨	프	피
ㅎ	하	햐	허	혀	호	효	후	휴	흐	히

Fig 2. Combination 1 consonant + 1 vowel

C. Convolutional Neural Network (CNN)

Convolutional Neural Network is a type of artificial neural network inspired by the functioning of the human brain's visual cortex [10]. CNN is developed as an evolution of the Multilayer Perceptron (MLP), specializing in processing two-dimensional grid-like data, such as images and videos [11]. CNN has many uses, especially in the fields of image and video processing, such as face recognition, object detection, image segmentation, and others [12]. This algorithm is highly popular due to its effective and efficient capability in processing data with large and complex grid structures.

CNNs leverage key image processing techniques such as convolution and pooling to enhance feature extraction and reduce computational complexity. Convolutional layers apply filters to input data to create feature maps, while pooling layers perform downsampling operations to reduce dimensionality, making the network more manageable and less prone to overfitting [13].

The stages of how CNN works are divided into two stages: feature learning (which consists of convolution, pooling, activation) and image classification (which consists of flatten layer, fully connected layer), as shown in Fig 3.

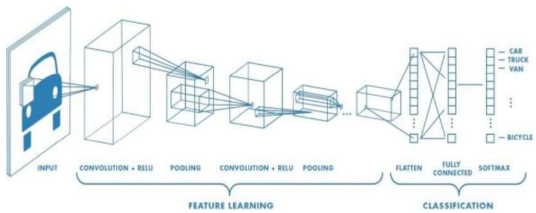

Fig 3. Convolutional Neural Network

D. Convolution Layer

Convolutional layer is a key block in feature learning and the CNN algorithm. In this layer, filters are applied to the incoming image to extract information and values from the previous layer. Filters come in various sizes depending on the type of CNN used, typically 3x3 in size, but there are also those sized 5x5 and 7x7 [10]. Filters or kernels are also commonly referred to as feature detectors, as indicated by the blue color in Fig 4.

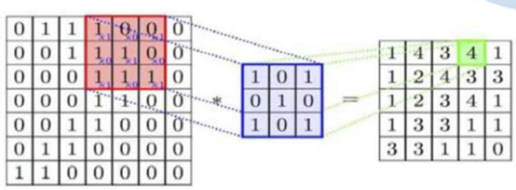

Fig 4. Multiplication with Feature Detector

E. Pooling Layer

Pooling is a layer in CNNs that serves to reduce spatial size so that the subsequent layers do not require excessive computation. This layer is also useful for addressing overfitting issues. There are many types of pooling, such as max pooling, min pooling, average pooling, stochastic pooling, spatial pyramid pooling [10]. The most commonly used pooling methods are max pooling and average pooling. Max pooling uses the highest value, while average pooling computes the average pixel value, as illustrated in Fig 5. However, this study utilizes max pooling.

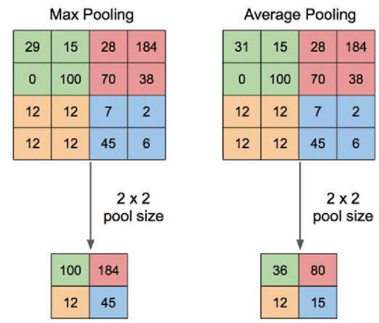

Fig 5. Max Pooling and Average Pooling

F. ReLu Activation

ReLU (Rectified Linear Unit) is used to convert negative values to zero. If the input to a neuron is negative, it will be converted to 0. For positive inputs, the value remains unchanged, meaning the output of the neuron will be the same as the input value itself. The formulation of ReLU shown in Equation 1.

$$f(x) = max\,(0, x) \tag{1}$$

G. Flatten Layer

The feature map generated in the previous process is in the form of a multidimensional array. However, in the fully connected layer, the input needed must be in the form of a vector. Therefore, a flatten layer is required. The Flatten Layer functions to reshape the matrix from the pooling layer into a single column (a single vector). The output of the flatten layer is a vector. Thus, these values can be used as input in the fully connected layer [14]. An illustration of the flatten layer shown in Fig 6.

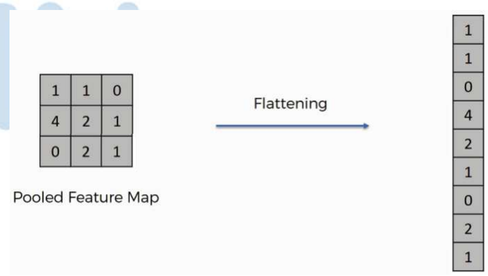

Fig 6. Flatten Layer

H. LeNet-5

LeNet-5 is one of the Convolutional Neural Network (CNN) architectures developed by Yann LeCun, Leon Bottou, Yoshua Bengio, and Patrick Haffner in 1998, primarily used for handwritten digit recognition tasks [15]. LeNet-5 consists of 7 layers, including convolutional layers, subsampling layers, followed by several fully connected layers. Despite its simplicity compared to contemporary architectures like VGG and ResNet, LeNet-5 laid the groundwork for subsequent developments in deep learning, influencing the design of neural networks for various image processing and classification tasks.

I. *Confusion Matrix*

Confusion Matrix is a performance measurement for classification problems in machine learning, presented in the form of a 4-table matrix that displays various combinations of predicted and actual values. Essentially, this matrix contains information that compares the system's classification results with the actual classification outcomes [16].

TABLE I. CONFUSION MATRIX

CLASS	*Classified as Positive*	*Classified as Negative*
Positive	TP	FN
Negative	FP	TN

There are 4 terms that represent the results of the classification process:

- TP (True Positive), which represents correctly detected positive data.
- FN (False Negative), which represents positive data incorrectly detected as negative.
- TN (True Negative), which represents correctly detected negative data.
- FP (False Positive), which represents negative data incorrectly detected as positive.

Using the values of TP, TN, FP, and FN, various performance evaluation metrics of the model such as precision, recall (sensitivity) can be calculated [17].

III. METHODOLOGY

A. *Object of Research*

This research focuses on detecting the writing of Hangul syllables on 'Learn Hangul' website to help students who aim to become proficient in write Korean letters into readable syllables. The output of 'Learn Hangul' website is the romanization of hangul syllables written by users.

The limitation of this research is that it only classifies Hangul syllables formed by one consonant letter combined with one vowel letter. Thus, each syllable is made up of two letters, as shown in Fig 2 (Chapter II, Subchapter B: Korean Syllables). The data is divided into 182 categories, corresponding to the number of syllables composed of two Hangul letters. Syllables used in this research are the basic forms of other Hangul syllables.

B. *CNN Model*

In this stage, the architecture of the model is designed based on the LeNet-5 network architecture, which is used to train Korean syllable image data.

TABLE II. OUTPUT SHAPE LENET-5

Layer	*Output Shape*	*Parameter*
Input image	**32,32,3**	-
conv2d	(*None*, 28, 28, 6)	456
max_pooling2d	(*None*, 14, 14, 6)	0
conv2d_1	(*None*, 10, 10, 16)	2416
max_pooling2d_1	(*None*, 5, 5 16)	0
conv2d_2	(*None*, 1, 1, 120)	48120
flatten	(*None*, 120)	0
dense	(*None, 84*)	10164
dense_1	(*None*, 182)	15470
Total params	:	**76626**
Trainable params	:	**76626**
Non-trainable params	:	**0**

The first layer is a convolutional layer with ReLU activation, using a 5x5 kernel size and 6 filters. It takes input images sized 32x32 and produces feature maps of size 28x28 with a depth of 6. The second layer is a max pooling layer with a 2x2 kernel, resulting in 6 feature maps sized 14x14. The third layer is another convolutional layer with ReLU activation, using a 5x5 kernel to generate 16 feature maps sized 10x10. The fourth layer is a max pooling layer with a 2x2 kernel, producing 16 feature maps sized 5x5. The fifth layer is the final convolutional layer with ReLU activation, using a 5x5 kernel to create 120 feature maps each of size 1x1. This is followed by a flatten layer to reshape the output into a vector. The sixth layer is a fully connected dense layer with 120 outputs. The seventh and final layer is also a fully connected layer, producing probabilities across 182 classes.

C. *Design System*

In this stage, two designs are created: system design and design for user flow. The system design shown in Fig 7.

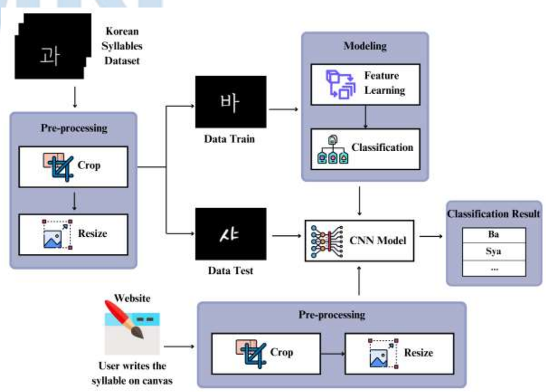

Fig 7. Design System

The first step is data pre-processing, where the data is cropped to remove empty spaces, leaving only the objects, and then resized to 32x32 to fit the CNN input. The dataset is then divided into training and testing data. Training data is used to train the system to recognize patterns and create a model, while testing data is used to evaluate the model's performance. Next, on the website, users write Korean syllables on the provided canvas. The system then processes the writing, starting with preprocessing steps including cropping and resizing the image to 32x32 pixels to fit the CNN model's input size. After preprocessing, the image is ready to be processed and classified using the CNN model.

User flow or steps that need to be taken by users in the Learn Hangul website shown in Fig 8.

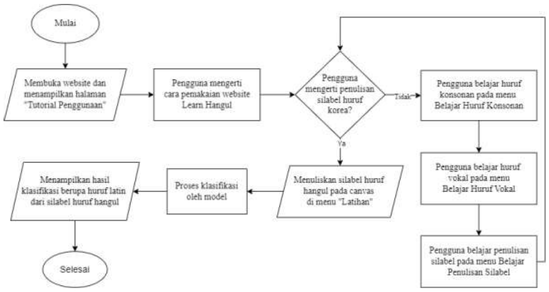

Fig 8. User flow

D. Data Preparation

To develop a model, a dataset is required. The data used is secondary data obtained from Kaggle.com. The data consists of grayscale images of Korean syllables sized 224 x 224 pixels, consists of 20,202 images of Korean Hangul syllables that composed of 2 characters (1 consonant + 1 vowel), divided into 182 labels with 111 images per label. The naming of these 182 classes is based on syllables consisting of 2 characters, such as "da", "dae", "de", "deo", "deu", "dya", "du", "do", and so on, following the conventions of writing Korean syllables.

In this study, the dataset is split into data train and data test with a ratio of 80:20. Details of the dataset split shown in Table III. Out of the total 20,202 images, 80% are used as training data, amounting to 16,198 images, and 20% are used as test data, totaling 4,004 images. Each label contains 89 train images and 22 test images.

TABLE III. DATASET DETAIL

	Qty	*%*	*Class*	*Data in 1 class*
Data Train	16.198 images	80%	182 class	89 images
Data Test	4004 images	20%	182 class	22 images

The data, which has been divided into folders according to their classes is ready to be used for developing a CNN model, and then uploaded it to Google Drive to be accessible through Google Colaboratory.

E. Pre-processing

The first step in this preprocessing is cropping. The dataset has a size of 224x224 pixels, as shown in Fig 9. This size is too large and contains too much meaningless black space.

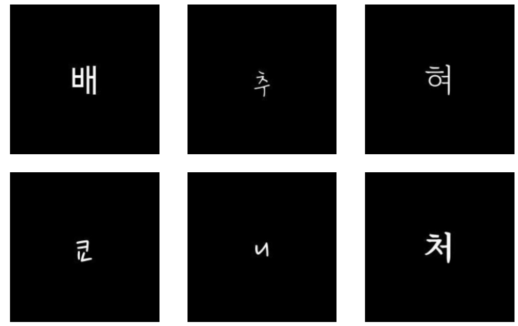

Fig 9. Dataset 224x224

This involves removing the black outer parts of the image, leaving only the object in the center. After removing the black space, the image is resized to 32x32 using the cv.resize() function from the OpenCV library. The results of the cropping and resizing shown in Fig 10.

Fig 10. Cropping data to 32x32px

The first step in feature extraction is Sobel edge detection. Feature extraction using edge detection is chosen to recognize the edges of objects in each image and highlight detailed parts of the image. Research by Widiawati found Sobel superior to Robert and Prewitt methods in detecting facial shapes and edge sharpness [18]. Thus, Sobel is used for edge detection in this study.

Fig 11 displays the original data before edge detection at the top and the data after applying Sobel edge detection at the bottom.

Fig 11. Result of Sobel Edge Detection

The second operation is morphological dilation, which expands or thickens objects to make them clearer. This process is necessary because the original dataset contains small and thin objects. Morphological dilation helps make these objects more visible and easier to analyze. Research by Anwariyah found that this operation effectively improves image quality and simplifies the segmentation of vehicle license plate characters [19]. Morphological dilation is performed by adding pixels to the edges of objects in the image.

The results shown in Fig 12, with the top section showing the data before dilation and the bottom section showing the data after morphological dilation.

Fig 12. Result of Morphological Dilation

F. Model Train Scenario

In this study, there are several scenarios for training the model by varying the batch size across three different datasets: the original dataset, the dataset with Sobel edge detection, and the dataset with morphological dilation operations. Batch size significantly impacts model train in machine learning. It refers to the number of data samples fed into the model during each training iteration. The training scenarios used in this study shown in Table IV.

TABLE IV. MODEL TRAIN SCENARIO

Name	*Data Pre-processing*	*Batch Size*
Dataset A	Crop + Resize	16
		32
		64
		128
		256
Dataset B	Crop + Resize + Sobel Edge Detection	16
		32
		64
		128
		256
Dataset C	Crop + Resize + Morphological Dilation	16
		32
		64
		128
		256

G. Testing

In this stage, testing of the system and application is conducted. Testing is crucial to ensure that the application meets requirements and functions properly without any defects. In this study, testing is conducted using 5 methods outlined as follows:

1) Manual testing: This involves evaluating the CNN model's ability to classify Korean syllables using data that not included in the training or test sets. The images used for this testing are handwritten Korean syllables by the researcher.

2) Confusion Matrix: Used to evaluate the performance of the CNN model.

3) Expert validation: Testing conducted with Korean language experts to ensure that the information conveyed in the website is accurate and does not mislead users.

4) Evaluating the usefulness of the Learn Hangul learning website by administering quizzes to users directly via Google Form, aimed at assessing the website's utility for users interested in learning Korean letters.

IV. RESULT AND DISSCUSSION

A. Model Train Result

In the first scenario, model training was conducted using dataset A, which underwent pre-processing with cropping and resizing only. The highest validation accuracy of 0.8923 was achieved with a batch size of 32, while the highest validation loss of 0.5066 was obtained with a batch size of 128.

Among the five model training sessions with dataset A (pre-processing Crop + Resize), larger batch sizes affected the accuracy results. The highest accuracy was achieved with a batch size of 32, but accuracy declined with batch sizes of 64 and larger. Although accuracy improved at a batch size of 256 compared to 128, it remained lower than the accuracy achieved with a batch size of 32. The results of the first scenario training are summarized in Table V.

TABLE V. RESULT OF TRAIN USING DATASET A

Dataset	*Batch Size*	*Loss*	*Accuracy*	*Val loss*	*Val accuracy*
A	16	0.2496	0.9179	0.3659	0.8911
	32	0.1269	0.9565	0.4074	0.8923
	64	0.2193	0.9265	0.3859	0.8867
	128	0.1983	0.9346	0.5066	0.8670
	256	0.2120	0.9318	0.4243	0.8798

In the second scenario, the dataset B underwent preprocessing steps including cropping, resizing, and Sobel edge detection. The highest validation accuracy, 0.8619, was achieved with a batch size of 16. Meanwhile, the highest validation loss, 0.6598, was reached with a batch size of 64.

Based on the training results with dataset B, using a larger batch size during model training affects accuracy. Similar to the first training scenario, the table shows that batch sizes from 32 to 256 have lower validation accuracy than batch size 16. Although accuracy improves at batch size 128, it still does not surpass the accuracy achieved with batch size 16. The training results for scenario B are summarized in Table VI.

TABLE VI. RESULT OF TRAIN USING DATASET B

Dataset	*Batch Size*	*Loss*	*Accuracy*	*Val loss*	*Val accuracy*
B	16	0.2866	0.9009	0.4882	0.8619
	32	0.2728	0.9054	0.4918	0.8553
	64	0.3955	0.8691	0.6598	0.8145
	128	0.2614	0.9138	0.4931	0.8565
	256	0.3166	0.8979	0.5647	0.8380

In the third training scenario, using dataset C involved preprocessing with cropping, resizing, and dilation morphological operations. The model achieved the highest validation accuracy of 0.8920 with a batch size of 32. Meanwhile, the lowest validation loss of 0.4103 was achieved with a batch size of 64.

Based on the training results with dataset C, the validation accuracy increased from batch size 16 to 32. However, it decreased from batch size 64 to 256. Although the accuracy increased again with batch size 256, it remained lower than the accuracy achieved in training with batch size 32. The outcomes of the third training scenario are summarized in Table VII.

TABLE VII. RESULT OF TRAIN USING DATASET C

Dataset	*Batch Size*	*Loss*	*Accuracy*	*Val loss*	*Val accuracy*
C	16	0.2554	0.9140	0.4736	0.8704
	32	0.1513	0.9472	0.4312	0.8920
	64	0.2470	0.9178	0.4103	0.8832
	128	0.2673	0.9106	0.5511	0.8447
	256	0.1587	0.9499	0.5058	0.8657

Next, three models with the highest accuracy were obtained from each training scenario. The highest accuracy was achieved with the original dataset, followed by the dataset with morphology dilation, and the lowest accuracy was observed in the model trained with the Sobel edge detection dataset. These results are summarized in Table VIII.

TABLE VIII. MODELS WITH HIGHEST ACCURACY

Dataset	*Batch Size*	*Val Loss*	*Val accuracy*
A	32	0.4074	0.8923
B	16	0.4882	0.8619
C	32	0.4312	0.8920

Among the scenarios, the lowest accuracy was observed with the Sobel edge detection dataset due to Hangul characters' smooth curves and strokes, which Sobel struggles to detect accurately, leading to disconnected or incorrect edges. Additionally, closely spaced or complex strokes in Hangul characters may cause Sobel to detect double edges, complicating character shape interpretation.

Similarly, models trained with the dilation morphology dataset showed lower accuracy than those trained with the original dataset, possibly because dilation could merge closely spaced or complex strokes in Hangul characters, reducing readability and causing recognition errors.

B. *User Interface Website Learn Hangul*

In this stage, which occurs after the model development phase, the website is built using the Flask framework, incorporating HTML, CSS, and JavaScript for front-end management, and Python for back-end operations.

The Practice Page or "Latihan" is a main feature of this website, designed for users to practice writing Hangul syllables consisting of 2 letters (1 consonant 1 vowel). This page appears when users click the "Latihan" button in the navigation bar. On this practice page, there is a black canvas where users can write Hangul syllables. Then there is a "Process Gambar" button, which is clicked after the user writes a Korean syllable on the canvas. After clicking the "Process Gambar" button, the romanization or alphabet letters of the syllable previously written by the user on the canvas will appear in the "Romanization" section. The layout of the practice page shown in Fig 13.

Fig 13. Practice Page of Website Learn Hangul

The learning page or "Belajar" on this website is designed for users who are not familiar with Hangul at all. This page features 3 menus: learning consonants, learning vowels, and learning how to write syllables. In addition to displaying the characters or forms of the letters, these menus also show the name of each letter, pronunciation guide, and instructions on how to write the letters.

The consonant learning page is a feature that users can utilize to recognize and learn Hangul consonants. Each letter on this page can be clicked to display a modal popup containing the letter's name, pronunciation rules, and writing method. As explained in the previous chapter, there are 14 consonant letters in Hangul, all of which are displayed on the entire consonant learning page in Fig 14.

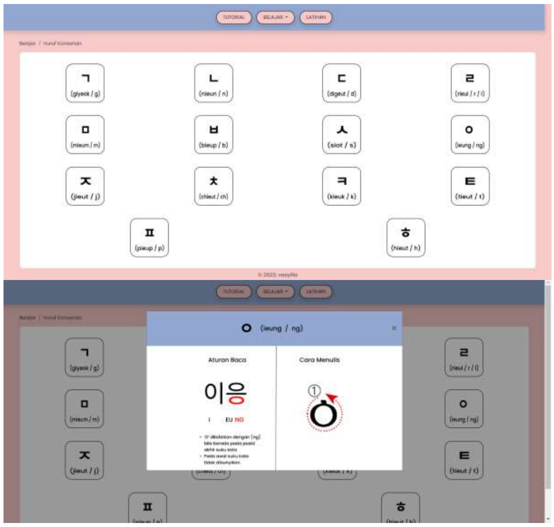

Fig 14. Learning Page of Consonant Letters

The next learning page is the vowel letters page, where users can learn and familiarize themselves with Hangul vowel letters. Similar to the previous menu for consonant letters, each letter on this menu can be clicked to display a pop-up modal with information on pronunciation and writing instructions. This menu showcases all 10 basic vowel letters and several expanded vowel letters (4), as shown in Fig 15.

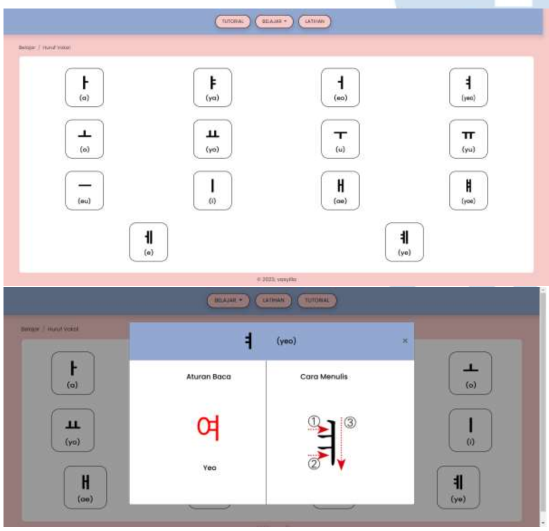

Fig 15. Learning Page of Vowel Letters

The third learning page is the syllable writing page. This page is useful for users to learn about syllable writing rules and the placement of each Hangul letter comprising 2 to 4 letters. This page can be seen in Fig 16.

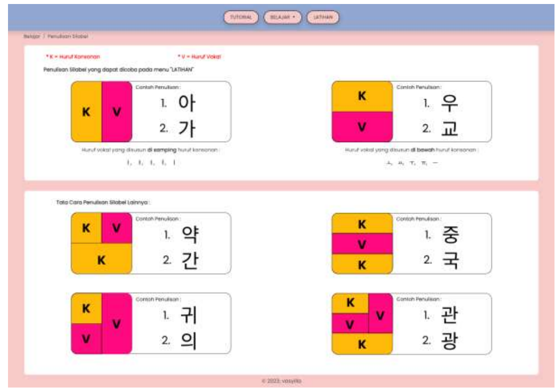

Fig 16. Learning Page of Syllable Structure

C. *Testing*

In this testing phase, the researcher conducted 5 tests: manual testing, confusion matrix, expert validation, black box, and direct user testing.

1) Manual Testing

In this manual testing stage, the researcher tested three models from Table VII. Only the models with the highest accuracy from each training scenario were subjected to manual testing. Out of 182 categories, the researcher selected 10 classes: Hya, Jyeo, Kyu, Tae, Rye, Dyo, Pi, Chu, Ga, and Se.

As shown in Figure 17, to test the model trained with Sobel edge detection data, images processed with Sobel edge detection were used. Similarly, for the model trained with dilation morphology data, images with dilation morphology were used for testing.

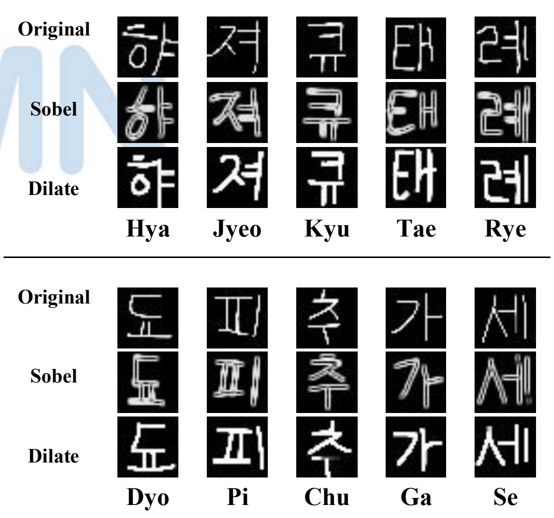

Fig 17. Image for Manual Testing

Each class consists of 10 images handwritten by the researcher and distinct from the dataset, resulting in a total of 100 images for this manual testing. The results of the manual testing shown in Table IX.

TABLE IX. RESULT OF MANUAL TESTING

Model	Class Syllable										Total
	Hya	Jyeo	Kyu	Tae	Rye	Dyo	Pi	Chu	Ga	Se	
A (Original)	9	6	8	6	9	8	6	10	9	6	77
B (Sobel)	6	5	9	5	4	10	7	10	7	7	70
C (Dilate)	9	8	9	6	9	9	6	3	5	8	72

Table IX shows how many times each model correctly predicted images according to their class. As mentioned earlier, each class contains 10 images. Therefore, a number 10 in the table indicates the model correctly predicted all images in that class. Out of 100 images used for testing, Model A, trained with the original dataset, correctly predicted 77 images. Thus, Model A, with an accuracy of 89.2%, is the best model for classifying Korean syllables and is used in the Learn Hangul website..

2) Confusion Matrix

The second test is the Confusion Matrix. Values from the confusion matrix can be used to calculate performance evaluation metrics such as precision, recall, and F1-score. This test aims to determine the percentage of correct predictions made by the model and is performed on the test data. Table X shows the results of the confusion matrix test for each class, with only a portion displayed.

TABLE X. CONFUSION MATRIX RESULT OF EACH CLASS

index	class	precission	recall	F1-score	support
0	A	0.81	0.77	0.79	22
1	Ae	0.91	0.91	0.91	22
2	Ba	0.90	0.86	0.88	22
3	Bae	1.00	0.91	0.95	22
4	Be	1.00	0.91	0.95	22
5	Beo	0.88	1.00	0.94	22
6	Beu	0.92	1.00	0.96	22
7	Bi	0.96	1.00	0.98	22
8	Bo	0.91	0.91	0.91	22
9	Bu	0.77	0.91	0.83	22
10	Bya	1.00	0.91	0.95	22
…	…	…	…	...	…
181	Yu	0.76	0.86	0.81	22

From the confusion matrix values in Table X, the final or average performance scores of Model A can be calculated. Below are the average calculations for precision, recall, and F1-score for the model.

$$Avg\ Precision = \frac{\Sigma\ precision\ seluruh\ class}{Total\ class} \tag{2}$$

$$Avg\ Precision = \frac{163.35}{182} = 0.897$$

Precision is an evaluation metric used to measure how accurate a model is in identifying positive data from all data classified as positive. The results above indicate that Model A has a precision score of 89.7%. A high precision value indicates that the model is effective in avoiding errors in classifying negative data as positive. However, there is still a 10.3% error rate, which can occur because the data used may contain noise, causing the model to learn incorrect patterns and leading to misclassifications.

$$Avg\ Recall = \frac{\Sigma\ recall\ seluruh\ class}{Total\ class} \tag{3}$$

$$Avg\ Recall = \frac{161.54}{182} = 0.8875$$

Recall, also known as sensitivity, is an evaluation metric used to indicate how well a model can accurately find all data belonging to the positive class. From the results above, it shows that Model A has a recall value of 88.8%. A high recall value indicates that the model is quite effective in detecting positive data. However, there is still a 11.2% error rate, which may occur due to variations in features distinguishing between positive and negative data that are not sufficiently understood by the model, or due to insufficient representation of positive data in the training set, which leads to the model being less trained in recognizing that class.

3) Expert Validation

In this testing, the expert (someone who proficient in the Korean language field) checked all content on the website, including verifying the writing of each Hangul letter and the arrangement of syllables displayed on the Learn Hangul website. Additionally, the expert also tested the main menu of the Learn Hangul website, specifically the Practice menu for writing Korean syllables.

In this testing scenario, the expert wrote 20 syllables: 10 in large size and 10 in small size. The expert then checked the classification results to see if they matched the Romanization displayed (classification results) or if there were any errors. The results of the testing with the expert can be seen in Table XI and Table XII

TABLE XI. TESTING RESULT WITH LARGE TEXT SIZE

Syllable written by the expert	*True Label*	*Predicted Label*	*Information*
아	A	A	True
뱌	Bya	Ba	False
차	Cha	Cha	True
도	Do	Do	True
주	Ju	Ju	True
미	Mi	Mi	True
리	Ri	Ri	True
사	Sa	Sa	True
서	Seo	Seo	True
요	Yo	Seo	False

TABLE XII. TESTING RESULT WITH SMALL TEXT SIZE

Syllable written by the expert	*True Label*	*Predicted Label*	*Information*
버	Beo	Beo	True
쳐	Chyeo	Ru	False
듀	Dyu	Chi	False
허	Heo	Chi	False
코	Ko	Pu	False
피	Pi	Ji	False
로	Ro	Po	False
서	Seo	Seo	True
우	U	Ho	False
여	Yeo	Ye	False

Based on the results in Table XI, by writing syllables in large and clear sizes, 8 out of 10 syllables were successfully classified correctly into their respective classes. However, the classification of the remaining 2 images was incorrect.

Based on the results from Table XII, where small-sized syllables were written, only 2 out of 10 images were correctly classified, while the other 8 images were classified into incorrect classes. This could happen because the images submitted to the model contained information that differed from what it had learned. When the input differs significantly from what the model has learned, such as images with very small information (Korean syllables) as shown in Table XI, it is likely to affect the classification results.

From this testing, it can be concluded that syllables written in small sizes on the canvas tend to result in misclassification or incorrect classification.

4) *Direct User Testing*

The last testing involved direct user testing. It was conducted by distributing questionnaires using Google Form to collect user response data. Two questionnaires were given to users: pre-learning and post-learning. The pre-learning questionnaire was completed by users before they tried learning on Learn Hangul website, while the post-learning questionnaire was filled out after they had used Learn Hangul website for learning.

In the pre-learning and post-learning questionnaires on Google Form, there are 5 questions identical to those in Table XIII. This approach aimed to observe changes in users' knowledge of Korean (Hangul) before and after using the Learn Hangul website.

TABLE XIII. QUIZ FOR USER

No.	Question	Point
1	The vowel letter "ㅔ" is placed ... the consonant letter	20
2	The vowel letter "ㅛ" is placed ... the consonant letter	20
3	What is the Latin letter equivalent of "ㅈ" ?	20
4	What is the Latin letter equivalent of "ㅍ" ?	20
5	What is the Latin letter of the syllable "저"?	20

Out of 20 participants, 16 showed an improvement in their scores compared to the pre-learning results. However, 4 respondents scored the same as in the pre-learning phase, indicating no improvement for these 4 individuals. The scores of the 20 respondents shown in Table XIV.

TABLE XIV. THE RESPONDENTS' SCORES

No	Res	Score		No	Res	Score	
		Pre	Post			Pre	Post
1.	Res.1	20	80	**11.**	Res.11	80	100
2.	Res.2	0	80	**12.**	Res.12	60	60
3.	Res.3	20	80	**13.**	Res.13	80	100
4.	Res.4	40	60	**14.**	Res.14	40	60
5.	Res.5	40	80	**15.**	Res.15	80	80
6.	Res.6	40	100	**16.**	Res.16	100	100
7.	Res.7	20	80	**17.**	Res.17	0	40
8.	Res.8	40	60	**18.**	Res.18	60	60
9.	Res.9	40	60	**19.**	Res.19	40	80
10.	Res.10	80	100	**20.**	Res.20	40	60

*Res = Respondent

Based on direct user testing, it was found that 80% of respondents experienced an increase in their knowledge of Korean (Hangul) letters after trying to learn them on the Learn Hangul website, while the remaining 20% did not experience any increase or decrease. These figures indicate the success of the Learn Hangul website in benefiting users who wish to learn Korean letters and show that it was fairly well-received by users.

V. CONCLUSION

Based on the results of the conducted research, several conclusions were drawn as follows: The CNN model with LeNet-5 architecture demonstrated the highest accuracy in identifying Korean Hangul syllables at 89.2% and achieved the greatest number of correct classifications in the manual testing conducted by Model A. The performance results of Model A, tested using a confusion matrix, indicated a precision value of 89.7% and a recall of 88.8%. Conversely, the CNN model with the lowest accuracy of 86% was observed in the second training scenario, which utilized dataset B with Sobel edge detection, and this model also recorded the lowest number of correct classifications in the manual testing. In the exercise menu on the Learn Hangul website, it is essential for writing to be clear and in large letters, as determined by expert testing, because it significantly influences the classification results. Lastly, 80% of respondents showed an improvement in their knowledge of Korean Hangul letters, whereas the remaining 20% exhibited no improvement or decline.

ACKNOWLEDGMENT

The author would like to express gratitude to State Polytechnic of Jember and the chief counselor for their support in this research.

REFERENCES

[1] U. Hasanah and M. Kharismawati, “Penggunaan Budaya Pop Korea dalam Proses Pembelajaran Bahasa Korea bagi Mahasiswa dengan Gaya Belajar Campuran,” *JLA (Jurnal Ling. Appl.*, vol. 3, no. 1, p. 10, 2020, doi: 10.22146/jla.52060.

[2] Mutiara, N. E. Prasatia, E. Evangeline, and N. H. Marhaeni, “Pengaruh Drama Korea Terhadap Minat Belajar Bahasa Korea Mahasiswa,” *Inov. J. Imiah Pengemb. Pendidik.*, vol. 1, no. 2, pp. 33–42, 2023, [Online]. Available: https://ejournal.lpipb.com/index.php/inovasi/article/view/20

[3] N. Leni, “Faktor yang Membuat 7 Negara (Finlandia, Korea Selatan, Hongkong, Jepang, Singapura , Belanda, Kanada) Diakui Memiliki Sistem Pendidikan Terbaik di Dunia dalam Kajian Antropologi dan Matematika,” *Pros. Semin. Nas. Mat. dan Pendidik. Mat.*, pp. 219–229, 2019.

[4] J. R. Cho and C. McBride, “Different Cognitive Correlates of Early Learning of Spelling of Different Target Types in Korean Hangul Among First Language Children and Adult Foreign Language Learners,” *J. Learn. Disabil.*, vol. 55, no. 2, pp. 138–153, 2022, doi: 10.1177/0022219420978231.

[5] C. Umam and L. B. Handoko, “Convolutional Neural Network (CNN) Untuk Identifkasi Karakter Hiragana,” *Pros. Semin. Nas. Lppm Ump*, vol. 0, no. 0, pp. 527–533, 2020, [Online]. Available: https://semnaslppm.ump.ac.id/index.php/semnaslppm/article/view/199

[6] C. A. Lorentius, R. Adipranata, and A. Tjondrowiguno, “Pengenalan Aksara Jawa dengan Menggunakan Metode Convolutional Neural Network,” *e-Proceeding Eng.*, vol. 7, no. 1, pp. 2558–2567, 2020.

[7] M. R. Alwanda, R. P. K. Ramadhan, and D. Alamsyah, “Implementasi Metode Convolutional Neural Network Menggunakan Arsitektur LeNet-5 untuk Pengenalan Doodle,” *J. Algoritm.*, vol. 1, no. 1, pp. 45–56, 2020, doi: 10.35957/algoritme.v1i1.434.

[8] K. Seon Jung, M. Min Kyung, P. Sung Tae, and H. Yung, *Buku Standar Bahasa Korea EPS-TOPIK*. 2015.

[9] M. Pastore, “Processing an Alphabetic Syllabary : Investigating the Orthographic Code for Korean Processing an Alphabetic Syllabary : Investigating the Orthographic Code for Korean,” 2019.

[10] A. Ajit, K. Acharya, and A. Samanta, “A Review of Convolutional Neural Networks,” *Int. Conf. Emerg. Trends Inf. Technol. Eng. ic-ETITE 2020*, pp. 1–5, 2020, doi: 10.1109/ic-ETITE47903.2020.049.

[11] T. Tinaliah, “Penerapan Convolutional Neural Network Untuk Klasifikasi Citra Ekspresi Wajah Manusia Pada MMA Facial Expression Dataset,” *JATISI (Jurnal Tek. Inform. dan Sist. Informasi)*, vol. 8, no. 4, pp. 2051–2059, 2021, doi: 10.35957/jatisi.v8i4.1437.

[12] Lusiana, A. A. Kurniasari, and I. F. Kusumawati, “Enhancing Accuracy in the Detection of Pneumonia in Adult Patients: An Approach by Using Convolutional Neural Networks BT - Proceedings of the 4th International Conference on Electronics, Biomedical Engineering, and Health Informatics,” T. Triwiyanto, A. Rizal, and W. Caesarendra, Eds., Singapore: Springer Nature Singapore, 2024, pp. 593–609.

[13] R. C. Gonzalez and R. E. Woods, “Digital Image Processing,” in *A Guide for Machine Vision in Quality Control*, Fourth., Addison Wesley Publishing Company, 2018, pp. 19–44.

[14] P. A. Nugroho, I. Fenriana, and R. Arijanto, "Implementasi Deep Learning Menggunakan Convolutional Neural Network (Cnn) Pada Ekspresi Manusia," *Algor*, vol. 2, no. 1, pp. 12–21, 2020.

[15] A. Faizin, M. Lutfi, and Achmyatari, "Perbandingan Arsitektur Lenet Dan Googlenet Dalam Klasifikasi Diabetic Retinopathy Pada Citra Retina Fundus," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 6, no. 1, pp. 342–347, 2022, doi: 10.36040/jati.v6i1.4581.

[16] N. Hadianto, H. B. Novitasari, and A. Rahmawati, "Klasifikasi Peminjaman Nasabah Bank Menggunakan Metode Neural Network," *J. Pilar Nusa Mandiri*, vol. 15, no. 2, pp. 163–170, 2019, doi: 10.33480/pilar.v15i2.658.

[17] M. Sholawati, K. Auliasari, and F. Ariwibisono, "Pengembangan Aplikasi Pengenalan Bahasa Isyarat Abjad Sibi Menggunakan Metode Convolutional Neural Network (Cnn)," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 6, no. 1, pp. 134–144, 2022, doi: 10.36040/jati.v6i1.4507.

[18] L. Widiawati and N. Wulandari, "Akurasi Deteksi Tepi Wajah dengan Metode Robert, Metode Prewitt Dan Metode Sobel," *J. Ilm. MIKA AMIK Al Muslim*, vol. 3, no. 2, pp. 79–87, 2019.

[19] K. Anwariyah, F. Sains, and D. Teknologi, "Deteksi Objek Nomor Kendaraan Pada Citra Kendaraan Bermotor (Detection of Vehicle License Objects in Motorized Vehicle Images)," *JTIM J. Teknol. Inf. dan Multimed.*, vol. 1, no. 4, pp. 311–317, 2020.