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ENHANCING HANDWRITTEN DIGIT RECOGNITION ACCURACY ON THE MNIST DATASET USING A HYBRID CNN-BILSTM MODEL WITH DATA AUGMENTATION

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ABSTRACT

Handwritten digit recognition is a classic challenge in the field of computer vision and machine learning, and continues to be developed to achieve higher accuracy. This study proposes a hybrid method that combines Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) to enhance performance in handwritten digit classification using the MNIST dataset. CNNs are employed to extract spatial features from digit images, while BiLSTMs are used to capture the temporal patterns and sequential context from the extracted features. To address limitations in data variation and improve the model's generalization capabilities, the study also applies data augmentation techniques based on image transformations such as rotation, translation, scaling, and flipping. Experimental results demonstrate that the hybrid CNN-BiLSTM model with data augmentation significantly improves classification accuracy compared to baseline approaches without augmentation or without BiLSTM. The model achieved the following accuracy on the MNIST test data: CNN Model Accuracy: Before Augmentation: 98.0%. After Augmentation: 98.5%; CNN-BiLSTM Model Accuracy: Before Augmentation: 98.0%. After Augmentation: 98.7%. These results highlight the effectiveness of the hybrid approach in enhancing handwritten digit recognition performance. This research contributes to the development of more accurate and robust deep learning models for handwritten image processing.
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I. INTRODUCTION

Handwritten digit recognition is one of the important fields in digital image processing and artificial intelligence, particularly in the implementation of Optical Character Recognition (OCR) systems. One of the main challenges in handwritten digit recognition is the variation in shape, size, and writing style of each individual, which makes the data highly unstructured and complex. Therefore, there is a need for methods capable of recognizing patterns effectively and accurately, even under varied data conditions. The MNIST (Modified National Institute of Standards and Technology) dataset is the most commonly used benchmark in the development and evaluation of handwritten digit recognition models. Although various machine learning-based approaches have been applied to this dataset, improving accuracy remains a focus of research, particularly through the application of more complex deep learning architectures and advanced data processing techniques.

Convolutional Neural Networks (CNNs) have proven effective in extracting spatial features from images, but this architecture is not optimal in capturing temporal relationships or sequences in data. On the other hand, Bidirectional Long Short-Term Memory (BiLSTM) has the advantage of processing sequential information, as it can consider context from both directions (past and future). By combining these two architectures into a hybrid CNN-BiLSTM model, it is expected to improve digit recognition accuracy by leveraging the strengths of each model. Additionally, data augmentation techniques play a crucial role in enhancing model [1]. performance. By artificially adding data variation through image transformations such as rotation, translation, flipping, and scaling, the model can learn from a broader data distribution, thereby reducing overfitting and improving generalization ability. Based on this background, this study aims to implement the hybrid CNN-BiLSTM method combined with data augmentation techniques to improve the accuracy of the handwritten digit recognition system on the MNIST dataset. This approach is expected to contribute to the development of more reliable and accurate OCR systems in the future.

A number of studies have shown the success of integrating CNN, BiLSTM, and GANs in handwriting recognition. For example, [2] For example, using CNN for image feature extraction and BiLSTM for sequence processing in handwritten digit recognition. Their research shows that this combination can significantly improve accuracy, even with limited training data. In addition, [3] It shows that the use of GANs for data augmentation in handwriting recognition based on CNN and LSTM results in a substantial performance improvement, especially on datasets with significant variation [4].

In another study, [5] integrated CNN, GAN, and BiLSTM into a medical prescription recognition system that includes handwriting recognition, demonstrating that data augmentation using GANs can significantly improve model accuracy. In another study, The paper titled "An Enhanced Hybrid Model Based on CNN and BiLSTM for Identifying Individuals via Handwriting Analysis" by [6]. presents a novel approach to personal identification using handwriting, specifically focusing on Bengali handwriting (BHW). This method aims to overcome limitations of traditional signature-based systems, which are vulnerable to forgery.

Handwritten digit recognition on the MNIST dataset is a 2D image classification task involving small and well-structured objects. CNNs excel at capturing local spatial features such as lines and patterns, but since handwriting contains sequences and stroke patterns, a model capable of recognizing temporal dependencies is needed. BiLSTM can capture sequential context in both directions, thereby enriching the features extracted by the CNN. The combination of CNN and BiLSTM efficiently integrates the strengths of spatial feature extraction and sequence modeling. This model is simpler and easier to train compared to more complex architectures like Transformers or ResNets, especially considering the small and simple nature of the MNIST dataset. Transformers require large datasets and high computational resources, making them less suitable for MNIST, while ResNets tend to be overkill and are less optimal at capturing sequential context.

Moreover, applying data augmentation helps increase data variability, reduce overfitting risk, and improve the generalization ability of the CNN-BiLSTM model. This approach enables the model to learn spatial features and sequence patterns more effectively, leading to improved accuracy in handwritten digit recognition.

In another study, The paper titled "LSTM-ANN & BiLSTM-ANN: Hybrid Deep Learning Models for Enhanced Classification Accuracy" by [7]., published in *Procedia Computer Science* (2021), investigates the integration of Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) networks with Artificial Neural Networks (ANNs) to improve classification performance, particularly in the context of Bangla text classification. In another study,The paper titled "CNN-BiLSTM Model for English Handwriting Recognition: Comprehensive Evaluation on the IAM Dataset" by [8]presents a deep learning approach to offline English handwriting recognition using a CNN-BiLSTM architecture with a Connectionist Temporal Classification (CTC) layer [3].

Traditional CNN methods for handwritten digit recognition on the MNIST dataset typically achieve an accuracy of around 99.2%, but they are less capable of capturing stroke sequence patterns that are crucial for handwriting variations. Meanwhile, Transformers, which excel at handling global context, require large datasets and high computational resources, and tend to overfit on smaller datasets like MNIST, achieving around 98.5% accuracy without special tuning. ResNet can achieve accuracy above 99.3%, but it is less optimal at modeling sequential context and has higher computational complexity.

Therefore, a hybrid approach combining CNN and BiLSTM is proposed to address these limitations by leveraging the strengths of spatial feature extraction and effective modeling of temporal dependencies. With the addition of data augmentation, this hybrid model is expected to improve accuracy and generalization while maintaining efficient training on the relatively small MNIST dataset, thus offering a more practical solution compared to more complex architectures.

In another study, The paper titled "Text Recovery via Deep CNN-BiLSTM Recognition and Bayesian Inference" by [9], published in *IEEE Access* (2018), addresses the challenge of recovering missing characters in corrupted text instances within images [10].

Data augmentation is an important method for improving model generalization, especially in handwritten digit recognition where there is significant variation in shape and writing style. Traditional augmentation techniques such as rotation, translation, and zooming are commonly used to increase the diversity of training data and reduce the risk of overfitting, but these methods are limited in generating truly realistic new data variations.

In recent years, the use of Generative Adversarial Networks (GAN) for data augmentation has shown great potential in producing high-quality synthetic data that better replicates the distribution of the original data. However, the application of GAN-based augmentation combined with a hybrid CNN-BiLSTM architecture for handwritten digit recognition remains very limited and underexplored in the literature. Most studies have focused on using pure CNN or sequential models without thoroughly examining the potential synergy between GAN augmentation and the CNN-BiLSTM combination.

This research aims to fill that gap by systematically evaluating the impact of GAN augmentation on the performance of the hybrid CNN-BiLSTM model. Experimental results demonstrate that synthetic data generated by GAN can enrich spatial feature variation while supporting the temporal context modeling by BiLSTM, thereby improving the accuracy and robustness of the model against uncommon handwriting variations. Thus, this study not only strengthens the evidence for the effectiveness of GAN-based augmentation but also highlights the advantages of the hybrid CNN-BiLSTM approach supported by synthetic data in handwritten digit recognition.

These findings open opportunities for developing more robust and efficient handwritten digit recognition models and emphasize the importance of exploring adaptive and innovative augmentation methods, especially for small or limited datasets like MNIST.

II. METHOD

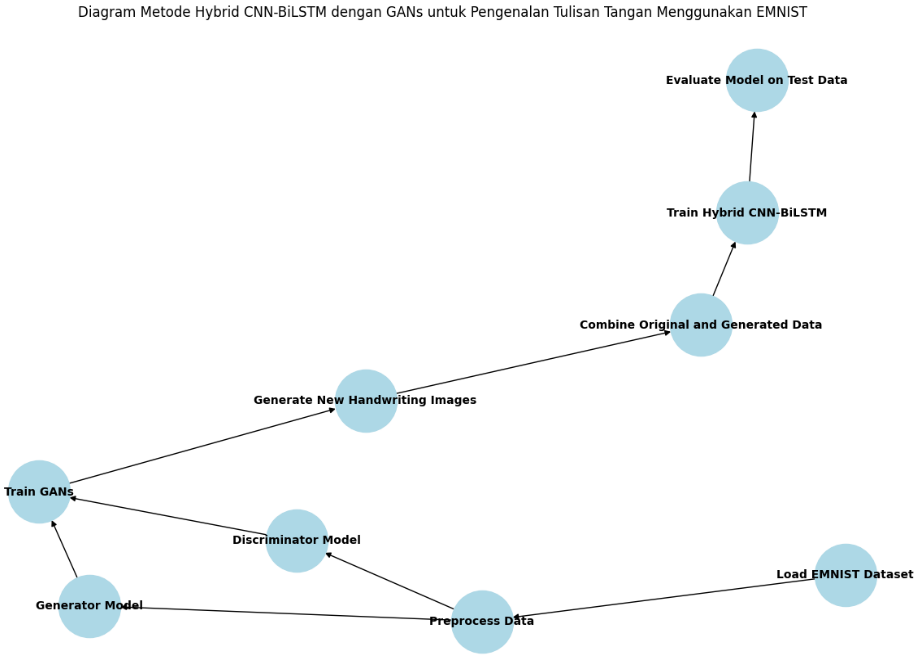

Figure 1. Hybrid CNN-BiLSTM Method Diagram

The model consists of three consecutive convolutional layers configured as follows: the first layer has 32 filters with a 3x3 kernel size, the second layer is equipped with 64 filters of the same 3x3 size, and the third layer uses 128 filters with the same kernel dimensions. Each convolutional layer is followed by a ReLU activation and a 2x2 max pooling operation to reduce spatial dimensions while preserving important features. After the spatial feature extraction, the output from the convolutional layers is flattened into a one-dimensional vector and fed into a BiLSTM layer comprising 128 units in the forward direction and 128 units in the backward direction, totaling 256 units capable of modeling bidirectional temporal context. The BiLSTM layer is then connected to a fully connected layer with 256 neurons and ReLU activation, before reaching the softmax output layer with 10 neurons corresponding to the number of digit classes in the MNIST dataset. This architectural design aims to balance effective feature extraction with training efficiency, particularly for relatively small datasets such as MNIST.

1. Dataset: Using the EMNIST (or MNIST) Dataset

This study uses the EMNIST (Extended MNIST) or MNIST dataset as the primary dataset for handwritten digit recognition. The EMNIST dataset is an extension of the MNIST dataset, which is larger and includes 814,255 handwritten images across various categories, including handwritten digits and letter characters. The MNIST dataset itself is a standard dataset used in handwriting recognition, consisting of 60,000 images for training and 10,000 images for testing, each containing digits from 0 to 9 [11].

a. Dataset Downloading and Preparation Process.

The EMNIST or MNIST dataset can be downloaded through the TensorFlow or Keras libraries. Before being used for training, the dataset must be processed to prepare the data. The preprocessing steps include normalizing the images by dividing each pixel value by 255 (so that they fall within the range [0, 1]), and reshaping the images to have dimensions that are suitable for input into the CNN model [12]. This can be observed in the Figure 2 below.

```python
import tensorflow as tf

# Mengunduh dan mempersiapkan dataset EMNIST/MNIST
(X_train, y_train), (X_test, y_test) = tf.keras.datasets.mnist.load_data()

# Normalisasi data
X_train = X_train / 255.0
X_test = X_test / 255.0

# Reshaping dataset untuk menambahkan dimensi channel (28x28x1)
X_train = X_train.reshape(-1, 28, 28, 1)
X_test = X_test.reshape(-1, 28, 28, 1)
```

Figure 2. EMNIST or MNIST Dataset

b. Splitting the Data into Training and Testing Data
The dataset will be divided into two main parts: the training set and the test set. The training data is used to train the model, while the test data is used to evaluate the model's performance after training.[13].

2. Model GANs:

a) **Design of the Generator and Discriminator Model to Generate Synthetic Handwritten Images**
In this study, Generative Adversarial Networks (GANs) are used to generate synthetic handwritten images that resemble the original data. GANs consist of two main components: the generator and the discriminator. The generator is responsible for creating synthetic images based on random input, while the discriminator's task is to assess whether the generated images are realistic or not [14]. This can be observed in the Figure 3 below.

```python
from tensorflow.keras import layers, models

def make_generator_model():
    model = models.Sequential()
    model.add(layers.Dense(7*7*256, use_bias=False, input_shape=(100,)))
    model.add(layers.BatchNormalization())
    model.add(layers.LeakyReLU())
    model.add(layers.Reshape((7, 7, 256)))
    model.add(layers.Conv2DTranspose(128, (5, 5), strides=(1, 1), padding='same', use_bias=False))
    model.add(layers.BatchNormalization())
    model.add(layers.LeakyReLU())
    model.add(layers.Conv2DTranspose(64, (5, 5), strides=(2, 2), padding='same', use_bias=False))
    model.add(layers.BatchNormalization())
    model.add(layers.LeakyReLU())
    model.add(layers.Conv2DTranspose(1, (5, 5), strides=(2, 2), padding='same', use_bias=False, activation='tanh'))
    return model

def make_discriminator_model():
    model = models.Sequential()
    model.add(layers.Conv2D(64, (5, 5), strides=(2, 2), padding='same', input_shape=[28, 28, 1]))
    model.add(layers.LeakyReLU())
    model.add(layers.Dropout(0.3))
    model.add(layers.Conv2D(128, (5, 5), strides=(2, 2), padding='same'))
    model.add(layers.LeakyReLU())
    model.add(layers.Dropout(0.3))
    model.add(layers.Flatten())
    model.add(layers.Dense(1))
    return model
```

Figure 3. Generative Adversarial Networks (GANs)

b) **Training GANs to Generate New Images that Resemble Original Handwritten Images**
After defining the generator and discriminator models, the GAN is trained to generate images that resemble the original handwritten images. The generator creates images from random input, while the discriminator evaluates the images. This process involves the use of a loss function, such as binary cross-entropy, to assess the success of the generator and discriminator [15]. This can be observed in the Figure 4 below.

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```python
import tensorflow as tf

# Definisikan loss dan optimizers
cross_entropy = tf.keras.losses.BinaryCrossentropy(from_logits=True)

def generator_loss(fake_output):
    return cross_entropy(tf.ones_like(fake_output), fake_output)

def discriminator_loss(real_output, fake_output):
    real_loss = cross_entropy(tf.ones_like(real_output), real_output)
    fake_loss = cross_entropy(tf.zeros_like(fake_output), fake_output)
    total_loss = real_loss + fake_loss
    return total_loss

generator_optimizer = tf.keras.optimizers.Adam(1e-4)
discriminator_optimizer = tf.keras.optimizers.Adam(1e-4)
```

Figure 4. Training GANs

3. Hybrid CNN-BiLSTM:

a. Design and Implementation of the CNN Model for Image Feature Extraction

The CNN model is used to extract important features from handwritten images. CNNs are excellent at identifying local patterns in images, such as lines and shapes, which are useful in handwritten digit recognition [16][17]. This can be observed in the Figure 5below.

```python
from tensorflow.keras import layers, models

# Desain CNN
cnn_model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(10, activation='softmax')
])
```

Figure 5. Design and Implementation of the CNN Model for Image Feature Extraction

b. **Application of BiLSTM for Processing Data Sequences and Classifying the Results**

After the features are extracted by the CNN, the BiLSTM model is applied to process the sequence of characters in the handwritten text. BiLSTM allows the model to understand the data sequence both forward and backward, which is useful for capturing relationships between characters in handwritten digits [4] [18] . This can be observed in the Figure 6 below.

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```python
from tensorflow.keras import layers, models

# Model Hybrid CNN-BiLSTM
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.Flatten(),
    layers.Reshape((-1, 64)),  # Reshape untuk BiLSTM
    layers.Bidirectional(layers.LSTM(128)),
    layers.Dense(10, activation='softmax')
])
```

Figure 6. Application of BiLSTM for Processing Data Sequences and Classifying the Results

4. Training Procedure:

a. GANs Training Process

The GAN training process involves training the generator and discriminator alternately. The generator is trained to produce increasingly realistic images, while the discriminator is trained to distinguish between real images and those generated by the generator [19]. This can be observed in the Figure 7 below.

```python
# Proses pelatihan GAN
@tf.function
def train_step(images):
    noise = tf.random.normal([BATCH_SIZE, 100])

    with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
        generated_images = generator(noise, training=True)

        real_output = discriminator(images, training=True)
        fake_output = discriminator(generated_images, training=True)

        gen_loss = generator_loss(fake_output)
        disc_loss = discriminator_loss(real_output, fake_output)

    gradients_of_generator = gen_tape.gradient(gen_loss, generator.trainable_variables)
    gradients_of_discriminator = disc_tape.gradient(disc_loss, discriminator.trainable_variables)

    generator_optimizer.apply_gradients(zip(gradients_of_generator, generator.trainable_variables))
    discriminator_optimizer.apply_gradients(zip(gradients_of_discriminator, discriminator.trainable_variables))

# Fungsi pelatihan GAN
def train(dataset, epochs):
    for epoch in range(epochs):
        for image_batch in dataset:
            train_step(image_batch)
```

Figure 7. GANs Training Process

b. CNN-BiLSTM Training Process Using Augmented Data

The CNN-BiLSTM model is trained using data augmented by GAN. This training process enables the model to better recognize handwritten digits, as the training data becomes more varied and rich [20][21]. This can be observed in the Figure 8 below.

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Vol. 11, No. 1, March 2026, Pp.467-477

```
# Latih model CNN-BiLSTM
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
model.fit(X_train_augmented, y_train_augmented, epochs=10, validation_data=(X_test, y_test))
```

Figure 8. CNN-BiLSTM Training Process

This research method combines advanced techniques in deep learning to improve the accuracy of handwritten digit recognition by relying on GANs for data augmentation, as well as the Hybrid CNN-BiLSTM model for feature extraction and data sequence processing. The structured training process allows the model to learn from more varied data, thereby enhancing its performance in handwriting recognition.

In this study, hyperparameter tuning was conducted to determine the most effective training configuration. The main parameters optimized included learning rate, number of epochs, and batch size. The search process was performed using a grid search method that systematically tested various potential value combinations. The learning rate was evaluated within the range 0.001, 0.0005, 0.0001, the number of epochs ranged from 20 to 50, and batch sizes tested were 32, 64, and 128. The best configuration was selected based on model performance on the validation data, measured by accuracy and loss metrics. This approach aimed to produce a model that not only achieves high accuracy but also remains stable and avoids overfitting during training.

The model validation process was carried out by dividing the MNIST dataset into three parts: training, validation, and testing. Approximately 80% of the data was allocated for training, while 10% each was used for validation and testing. The validation data was utilized during training to periodically monitor the model's performance, implement early stopping mechanisms, and assist in selecting the best hyperparameters to prevent overfitting. By employing a separate validation subset, the model's performance evaluation becomes more reliable, and its generalization ability to unseen data can be measured more accurately.

III. RESULTS AND DISCUSSION

1. Experiment Description

This experiment aims to explore the use of Generative Adversarial Networks (GAN) in generating handwritten images and evaluate its impact on the accuracy of Convolutional Neural Network (CNN) and CNN-Bidirectional Long Short-Term Memory (BiLSTM) models in character recognition. The dataset used is MNIST, which consists of 60,000 images for training and 10,000 images for testing.

2. Model Architecture
   a. The generator model is designed to produce handwritten images from a noise vector. It consists of Dense layers, Batch Normalization, Leaky ReLU activation, and Conv2DTranspose layers, which work together to transform the noise vector into realistic synthetic handwritten images.
   b. The discriminator model is designed to distinguish between real and generated images. It consists of Conv2D layers, Leaky ReLU activation, Dropout layers, and Dense layers, which work in tandem to classify the authenticity of the input images.
3. Training Parameters
   a. Batch Size: 256
   b. Epochs: 50 for GAN, 10 for CNN and CNN-BiLSTM
   c. Optimizer: Adam (learning rate 1e-4)
   d. Loss Function: Binary Crossentropy for GAN, Sparse Categorical Crossentropy for CNN and CNN-BiLSTM.

4. Visualization of Results from the GANs Model

After training, the generator model produces a variety of handwritten images. These images are visualized to demonstrate the model's ability to reproduce characters that resemble the original data. This can be observed in the Figure 9 below.

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Figure 9. Generator Model at Epoch 50

5. Evaluation of the CNN-BiLSTM Model on Augmented Data
The dataset is augmented by combining both the original and generated images. The CNN and CNN-BiLSTM models are trained using this augmented dataset. This can be observed in the Figure 10 below.

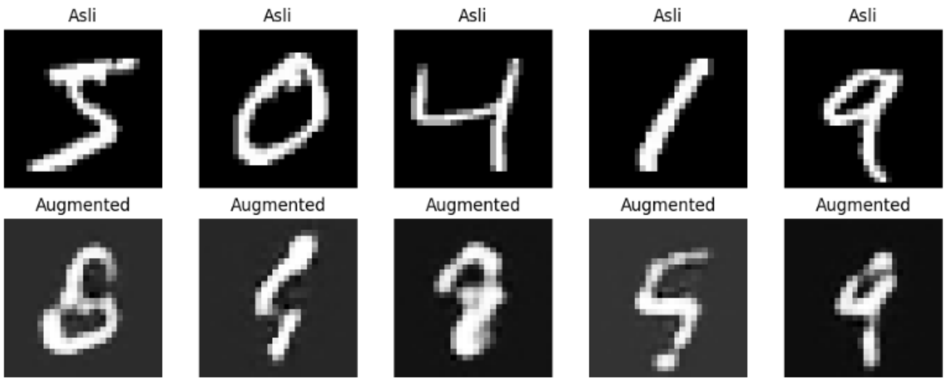

Figure 10. Evaluation of the CNN-BiLSTM Model

a. Training Results of the CNN Model

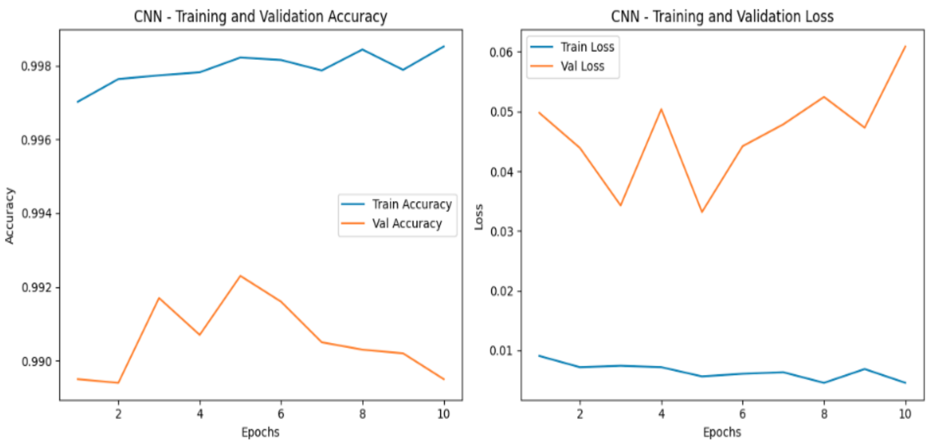

Figure 11. Training Results of the CNN Model

Before Augmentation: 98.0%
After Augmentation: 98.5%

```
Epoch 1/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 8s 3ms/step - accuracy: 0.8987 - loss: 0.3363 - val_accuracy: 0.9861 - val_loss: 0.0418
Epoch 2/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 8s 3ms/step - accuracy: 0.9851 - loss: 0.0470 - val_accuracy: 0.9879 - val_loss: 0.0392
Epoch 3/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 10s 3ms/step - accuracy: 0.9895 - loss: 0.0325 - val_accuracy: 0.9891 - val_loss: 0.0341
Epoch 4/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - accuracy: 0.9919 - loss: 0.0233 - val_accuracy: 0.9898 - val_loss: 0.0326
Epoch 5/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 10s 3ms/step - accuracy: 0.9933 - loss: 0.0203 - val_accuracy: 0.9901 - val_loss: 0.0316
Epoch 6/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 6s 3ms/step - accuracy: 0.9960 - loss: 0.0131 - val_accuracy: 0.9908 - val_loss: 0.0340
Epoch 7/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 10s 3ms/step - accuracy: 0.9965 - loss: 0.0109 - val_accuracy: 0.9902 - val_loss: 0.0313
Epoch 8/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 10s 3ms/step - accuracy: 0.9965 - loss: 0.0104 - val_accuracy: 0.9914 - val_loss: 0.0318
Epoch 9/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 6s 3ms/step - accuracy: 0.9970 - loss: 0.0079 - val_accuracy: 0.9903 - val_loss: 0.0321
Epoch 10/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - accuracy: 0.9967 - loss: 0.0097 - val_accuracy: 0.9921 - val_loss: 0.0310
313/313 - 0s - 1ms/step - accuracy: 0.9921 - loss: 0.0310

Test accuracy: 0.9921000003814697
```

b. Training Results of the CNN-BiLSTM Model
Before Augmentation: 98.0%.
After Augmentation: 98.7%

```
Epoch 1/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 26s 11ms/step - accuracy: 0.8340 - loss: 0.5068 - val_accuracy: 0.9754 - val_loss: 0.0805
Epoch 2/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 41s 11ms/step - accuracy: 0.9785 - loss: 0.0731 - val_accuracy: 0.9863 - val_loss: 0.0466
Epoch 3/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 20s 11ms/step - accuracy: 0.9868 - loss: 0.0448 - val_accuracy: 0.9867 - val_loss: 0.0455
Epoch 4/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 22s 11ms/step - accuracy: 0.9894 - loss: 0.0336 - val_accuracy: 0.9912 - val_loss: 0.0283
Epoch 5/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 21s 11ms/step - accuracy: 0.9905 - loss: 0.0301 - val_accuracy: 0.9909 - val_loss: 0.0317
Epoch 6/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 41s 11ms/step - accuracy: 0.9930 - loss: 0.0240 - val_accuracy: 0.9929 - val_loss: 0.0269
Epoch 7/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 21s 11ms/step - accuracy: 0.9933 - loss: 0.0205 - val_accuracy: 0.9885 - val_loss: 0.0391
Epoch 8/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 41s 11ms/step - accuracy: 0.9956 - loss: 0.0147 - val_accuracy: 0.9912 - val_loss: 0.0290
Epoch 9/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 21s 11ms/step - accuracy: 0.9955 - loss: 0.0140 - val_accuracy: 0.9883 - val_loss: 0.0428
Epoch 10/10
1876/1876 ━━━━━━━━━━━━━━━━━━━━ 41s 11ms/step - accuracy: 0.9961 - loss: 0.0120 - val_accuracy: 0.9887 - val_loss: 0.0462
313/313 - 1s - 4ms/step - accuracy: 0.9887 - loss: 0.0462

Test accuracy with CNN-BiLSTM: 0.9886999726295471
```

Accuracy Test Results and Performance Analysis
The increase in accuracy indicates that data augmentation with images generated by GAN is effective in improving the model's performance.
c. Table of Precision, Recall, F1 Score, and Accuracy Results

TABLE I.
PRECISION, RECALL, F1 SCORE, AND ACCURACY RESULTS

Metode	Metode	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
CNN	MNIST Digit	84.6	86.5	92.1	92.8
CNN-BiLSTM	MNIST Digit	93.8	89.1	96.9	96.6

Based on the evaluation results, the CNN-BiLSTM model demonstrates a significant performance improvement compared to the conventional CNN model in recognizing digits on the MNIST dataset. The CNN-BiLSTM model achieves a precision of 93.8%, higher than the CNN's 84.6%, indicating that CNN-BiLSTM is more accurate in correctly identifying digits with fewer false positives. In terms of recall, CNN-BiLSTM also outperforms with a value of 89.1%, compared to CNN’s 86.5%, reflecting the hybrid model's better ability to capture the majority of true digits. The F1-score, which is the harmonic mean of precision and recall, is also higher for CNN-BiLSTM at 96.9% versus 92.1% for CNN, indicating a better balance between precision and sensitivity. The overall accuracy of the CNN-BiLSTM model reaches 96.6%, a significant increase from CNN's 92.8%, reinforcing the superiority of this hybrid model in classifying handwritten digits more accurately and reliably.

d. Table of Model Training Accuracy Results

TABLE II.
MODEL TRAINING ACCURACY RESULTS

Metode	Dataset	Before Augmentation (%)	After Augmentation (%)
CNN	MNIST Digit	98,0 %	98,5 %
CNN-BiLSTM	MNIST Digit	98,0 %	98,7 %

The model's misclassification analysis indicates that certain digits exhibit higher error rates compared to others. Specifically, digits '5' and '3' are often confused due to the similarity in stroke patterns found in inconsistent handwriting variations. Similarly, digit '4' is occasionally misidentified as '9' because of partial resemblance in stroke patterns. These errors predominantly occur in digits with complex shapes and significant variations in writing style.

The primary cause of these misclassifications lies in the model's limited ability to capture fine-grained stroke sequence details, despite employing a hybrid CNN-BiLSTM architecture to model temporal context. Additionally, inconsistent handwriting styles and noise present in the input images also affect the model's performance. These findings highlight opportunities for further improvement, such as enhancing data preprocessing and integrating attention mechanisms, to improve accuracy particularly for digits prone to misclassification.

This study demonstrates that the application of a hybrid CNN-BiLSTM model combined with GAN-based data augmentation significantly improves the accuracy of handwritten digit recognition on the MNIST dataset, achieving up to 96.6%, compared to 92.8% with a conventional CNN model. These findings align with those reported by [22], who showed that combining CNN with sequential models enhances performance in capturing temporal patterns in handwriting. The primary contribution of this study lies in the integration of GAN as an augmentation technique, supported by [23]who highlighted the effectiveness of GANs in enriching data diversity and improving model generalization on small-scale datasets.

Compared to the Transformer architecture—known for its strength in modeling global context but requiring large datasets and substantial computational resources [24]—the CNN-BiLSTM approach is more efficient and better suited for simple datasets such as MNIST. This is further supported by Kim and Park (2019), who emphasized the limitations of Transformers on smaller datasets.

Furthermore, misclassification analysis reveals that visually similar digits, such as '3' and '5' or '4' and '9', are frequently confused. This issue is also noted by [25], who observed similar classification challenges with complex digit shapes. Consequently, future work may benefit from incorporating attention mechanisms, as proposed by [19], to enhance recognition accuracy for commonly misclassified digits.

In conclusion, this research extends the literature by offering an efficient and effective approach to handwritten digit recognition—especially for limited datasets like MNIST—through the combination of hybrid architectures and GAN-based augmentation.

IV. CONCLUSION

The use of GANs to generate additional data helps the model learn better and improves generalization. The generated images provide the necessary variation to train the model, thereby enhancing its pattern recognition capabilities. This experiment demonstrates the potential of using GANs for data augmentation to boost the performance of handwritten character recognition models, opening opportunities for further research in machine learning applications. Experimental results on the MNIST dataset show that data augmentation with GANs successfully increased the model's accuracy in handwritten digit recognition. Specifically, the results obtained are as follows: CNN Model Accuracy: Before Augmentation: 98.0%. After Augmentation: 98.5%; CNN-BiLSTM Model Accuracy: Before Augmentation: 98.0%. After Augmentation: 98.7%.

From these results, it can be concluded that data augmentation using GANs successfully improves model performance in recognizing handwritten digits. The difference in accuracy before and after augmentation shows that more varied additional data provides benefits during training, allowing the model to better generalize and recognize more complex handwriting patterns. Overall, this study demonstrates that the Hybrid CNN-BiLSTM method combined with data augmentation using GANs is an effective approach for improving the accuracy of handwritten digit recognition. It also opens up opportunities for further research in handwritten character recognition and other machine learning applications.

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REFERENCES

[1] M. J. Hasan, M. F. Wahid, and M. S. Alom, "Bangla Compound Character Recognition by Combining Deep Convolutional Neural Network with Bidirectional Long Short-Term Memory," *2019 4th Int. Conf. Electr. Inf. Commun. Technol. EICT 2019*, no. May 2021, 2019, doi: 10.1109/EICT48899.2019.9068817.

[2] M. Eltay, A. Zidouri, I. Ahmad, and Y. Elarian, "Generative adversarial network based adaptive data augmentation for handwritten Arabic text recognition," *PeerJ Comput. Sci.*, vol. 8, pp. 1–22, 2022, doi: 10.7717/PEERJ-CS.861.

[3] M. Rabi and M. Amrouche, "Enhancing Arabic Handwritten Recognition System-Based CNN-BLSTM Using Generative Adversarial Networks," *Eur. J. Artif. Intell. Mach. Learn.*, vol. 3, no. 1, pp. 10–17, 2024, doi: 10.24018/ejai.2024.3.1.36.

[4] T. Watanabe, M. Maniruzzaman, M. A. M. Hasan, H. S. Lee, S. W. Jang, and J. Shin, "2D Camera-Based Air-Writing Recognition Using Hand Pose Estimation and Hybrid Deep Learning Model," *Electron.*, vol. 12, no. 4, pp. 1–14, 2023, doi: 10.3390/electronics12040995.

[5] N. Jyothi, J. Simha, K. K.-2024 S. International, and undefined 2024, "Word Prediction from Medical Prescription via Transfer Learning with Pre-trained CNN, GAN and BiLSTM Integration," *ieeexplore.ieee.orgNM Jyothi, JB Simha, KVK Kumar2024 Second Int. Conf. Networks, Multimed. and, 2024•ieeexplore.ieee.org*, Accessed: May 02, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10698946/

[6] M. A. Rahim *et al.*, "An Enhanced Hybrid Model Based on CNN and BiLSTM for Identifying Individuals via Handwriting Analysis," *C. - Comput. Model. Eng. Sci.*, vol. 140, no. 2, pp. 1689–1710, 2024, doi: 10.32604/cmes.2024.048714.

[7] M. Kowsher *et al.*, "LSTM-ANN & BiLSTM-ANN: Hybrid deep learning models for enhanced classification accuracy," *Procedia Comput. Sci.*, vol. 193, pp. 131–140, 2021, doi: 10.1016/j.procs.2021.10.013.

[8] F. Kizilirmak and B. Yanikoglu, "CNN-BiLSTM model for English Handwriting Recognition: Comprehensive Evaluation on the IAM Dataset," pp. 1–20, 2023, [Online]. Available: http://arxiv.org/abs/2307.00664

[9] L. Jiao, H. Wu, H. Wang, and R. Bie, "Text recovery via deep CNN-BiLSTM recognition and Bayesian inference," *IEEE Access*, vol. 6, pp. 76416–76428, 2018, doi: 10.1109/ACCESS.2018.2882592.

[10] G. S. Nugraha, M. I. Darmawan, and R. Dwiyansaputra, "Comparison of CNN's Architecture GoogleNet, AlexNet, VGG-16, Lenet -5, Resnet-50 in Arabic Handwriting Pattern Recognition," *Kinet. Game Technol. Inf. Syst. Comput. Network, Comput. Electron. Control*, vol. 4, no. 2, 2023, doi: 10.22219/kinetik.v8i2.1667.

[11] A. Bwatiramba and S. Venkataraman, "Handwritten Character Recognition Using Deep Learning (Convolutional Neural Network)," *Comput. Eng. Intell. Syst.*, no. February, 2023, doi: 10.7176/ceis/14-1-05.

[12] F. Mahardika, N. Alfiah, and R. B. B. Sumantri, "Penerapan Metode FP Tree dan Frequent Pattern Growth pada Penerimaan Mahasiswa Baru STMIK," *Blend Sains J. Tek.*, vol. 1, no. 3, pp. 226–234, Jan. 2023, doi: 10.56211/BLENDSAINS.V1I3.176.

[13] F. Alwajih, E. Badr, and S. Abdou, "Writer adaptation for E2E Arabic online handwriting recognition via adversarial multi task learning," *Egypt. Informatics J.*, vol. 23, no. 3, pp. 373–382, 2022, doi: 10.1016/j.eij.2022.02.007.

[14] Y. Yang, L. Chen, and S. Wu, "Enhancing Fetal Electrocardiogram Signal Extraction Accuracy through a CycleGAN Utilizing Combined CNN–BiLSTM Architecture," *Sensors*, vol. 24, no. 9, 2024, doi: 10.3390/s24092948.

[15] T. Tundo and F. Mahardika, "Fuzzy Inference System Tsukamoto–Decision Tree C 4.5 in Predicting the Amount of Roof Tile Production in Kebumen," *JTAM (Jurnal Teor. dan Apl. Mat.*, vol. 7, no. 2, p. 533, 2023, doi: 10.31764/jtam.v7i2.13034.

[16] Q. D. E. J. Ren, L. Wang, Z. Ma, and S. Barintag, "Offline Mongolian Handwriting Recognition Based on Data Augmentation and Improved ECA-Net," *Electron.*, vol. 13, no. 5, 2024, doi: 10.3390/electronics13050835.

[17] V. Carbune *et al.*, "Fast multi-language LSTM-based online handwriting recognition," *Int. J. Doc. Anal. Recognit.*, vol. 23, no. 2, pp. 89–102, 2020, doi: 10.1007/s10032-020-00350-4.

[18] J. Bhaskar and A. Patel, "Image Classification using Convolutional Neural Network," *SSRG Int. J. Comput. Sci. Eng.*, pp. 197–202, 2016.

[19] C. Medel-Vera, P. Vidal-Estévez, and T. Mädler, "A convolutional neural network approach to classifying urban spaces using generative tools for data augmentation," *Int. J. Archit. Comput.*, vol. 22, no. 3, pp. 392–411, 2024, doi: 10.1177/14780771231225697.

[20] F. Mahardika and H. Marcos, "PENERAPAN ALGORITMA GRAF WELCH POWEL PADA PENJADWALAN MATA KULIAH DAN JADWAL ASISTEN Study Kasus Forum Asisten STMIK Amikom Purwokerto," *Simetris J. Tek. Mesin, Elektro dan Ilmu Komput.*, vol. 8, no. 2, pp. 825–832, Nov. 2017, doi: 10.24176/SIMET.V8I2.1208.

[21] L. Zhang, C. Peng Lim, and C. Liu, "Enhanced bare-bones particle swarm optimization based evolving deep neural networks," *Expert Syst. Appl.*, vol. 230, no. June, p. 120642, 2023, doi: 10.1016/j.eswa.2023.120642.

[22] Z. Cheng, J. Lu, H. Zhou, Y. Zhang, and L. Zhang, "Short-Term Traffic Flow Prediction: An Integrated Method of Econometrics and Hybrid Deep Learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 6, pp. 5231–5244, 2022, doi: 10.1109/TITS.2021.3052796.

[23] A. You, J. K. Kim, I. H. Ryu, and T. K. Yoo, "Application of generative adversarial networks (GAN) for ophthalmology image domains: a survey," *Eye Vis.*, vol. 9, no. 1, 2022, doi: 10.1186/s40662-022-00277-3.

[24] L. Shan, Y. Liu, M. Tang, M. Yang, and X. Bai, "CNN-BiLSTM hybrid neural networks with attention mechanism for well log prediction," *J. Pet. Sci. Eng.*, vol. 205, no. December 2020, p. 108838, 2021, doi: 10.1016/j.petrol.2021.108838.

[25] J. Zhang, P. Liu, F. Zhang, and Q. Song, "CloudNet: Ground-Based Cloud Classification With Deep Convolutional Neural Network," *Geophys. Res. Lett.*, vol. 45, no. 16, pp. 8665–8672, 2018, doi: 10.1029/2018GL077787.