Building A Basic Neural Network

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***Abstract*—This paper provides an introduction to building a basic neural network, highlighting key components such as input, hidden, and output layers, along with the essential mathematical operations involved. We discuss the role of activation functions, including ReLU and softmax, in enabling non-linear transformations crucial for pattern recognition. The backpropagation process and gradient descent optimization are explored as core mechanisms for reducing error and improving accuracy. Using the MNIST dataset, we demonstrate the network's implementation and training, achieving notable accuracy improvements through iterative learning. This foundational overview serves as a stepping stone for understanding more complex neural network architectures.**

***Index Terms*—Neural Network, Artificial Intelligence, Machine Learning, Backpropagation, Gradient Descent, Activation Function, ReLU, Softmax, Cross-Entropy Loss, MNIST, Python, TensorFlow, Image Classification, Supervised Learning, Model Training**

I. Introduction

In recent years, artificial neural networks (ANNs) have revolutionized numerous fields, including image recognition, natural language processing, and predictive analytics. At the core of these advances lies the fundamental building block: the neural network. This article delves into the essentials of constructing a basic neural network, breaking down each component and step necessary to understand how this powerful tool functions. While more complex variations such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are often employed for specialized tasks, building a basic neural network serves as a foundational exercise. It provides critical insights into how neural networks process information, learn patterns, and make predictions.

A neural network can be likened to the structure of the human brain, where neurons—each connected to several other neurons—communicate through electrical signals. In a similar fashion, ANNs are composed of artificial neurons arranged in layers that collectively contribute to the processing of input data, transformation through hidden layers, and ultimately prediction or classification in the output layer. These artificial neurons, often referred to as nodes or units, are organized into three main types of layers: the input layer, hidden layers, and the output layer.

- The Input Layer is the entry point for data into the neural network. Here, each node represents a feature or a dimension of the input data. For instance, in an image recognition task, each pixel of an image would be an individual input to the network.
- Hidden Layers lie between the input and output layers, and are crucial for enabling the network to capture complex patterns within the data. Depending on the complexity of the task, there could be one or multiple hidden layers, each with its own set of neurons. These layers perform various transformations on the input data through weighted connections and activation functions, allowing the network to learn non-linear patterns.
- The Output Layer provides the final prediction or classification result. The number of neurons in this layer corresponds to the number of possible classes or the dimensions of the output. For example, in a digit classification task, the

output layer might contain ten neurons, one for each digit from 0 to 9.

In constructing a basic neural network, understanding the role of weights and biases is essential. Each connection between neurons has an associated weight, which indicates the strength or importance of that connection. During the training process, the network adjusts these weights to minimize the difference between the predicted outputs and the actual targets. Additionally, each neuron has a bias term that allows it to shift the activation function, providing the network with greater flexibility to model complex relationships.

Activation Functions play a vital role in introducing non-linearity into the network. Without non-linear activation functions, a neural network would simply be a linear model, regardless of the number of layers. Popular activation functions include the Rectified Linear Unit (ReLU), which sets all negative values to zero while maintaining positive values as they are, and the Sigmoid function, which maps values to a range between 0 and 1, making it suitable for binary classification tasks. Activation functions enable the network to learn and model a variety of complex patterns in data by stacking multiple layers with non-linear transformations.

A core aspect of training a neural network is the process of backpropagation, which involves adjusting the weights and biases based on the error of the network's predictions. The error is calculated using a loss function, such as Mean Squared Error (MSE) for regression tasks or Cross-Entropy for classification tasks. By calculating the gradient of the loss function with respect to each weight and bias, the network is able to iteratively update these parameters, minimizing the error through an optimization algorithm like Gradient Descent or its more advanced variants, such as Adam. These adjustments allow the neural network to gradually improve its accuracy over many iterations or epochs.

Building a basic neural network also requires an understanding of hyperparameters, which govern aspects of the network's structure and training process, such as the learning rate, the number of epochs, and the batch size. The learning rate determines the step size during the parameter updates, balancing between convergence speed and stability. A high learning rate may lead to rapid but unstable updates, while a low learning rate might be stable but slow. The number of epochs specifies how many times the network will pass through the entire training dataset, and the batch size defines the number of samples the network processes before updating the weights. Tuning these hyperparameters is essential for achieving optimal performance and avoiding issues like overfitting or underfitting.

In summary, building a basic neural network is a process that requires a balance of understanding both theoretical concepts and practical implementation. Each element—whether it is the structure of layers, the selection of activation functions, or the tuning of hyperparameters—contributes to the network's ability to learn from data and make accurate predictions. Despite the simplicity of basic neural networks, they form the groundwork for more sophisticated architectures and applications, making them an essential step in the journey toward mastering deep learning.

II. Introduction to Handwritten Digit Recognition (MNIST)

A. *Overview*

Handwritten digit recognition is a classic problem in the fields of computer vision and machine learning. This task requires a computer system to accurately identify and classify handwritten digits from 0 to 9. The handwritten digit data is commonly stored in the MNIST (Modified National Institute of Standards and Technology) dataset, which is one of the most popular datasets for research and development of machine learning algorithms.

B. *Main idea*

Handwritten digit recognition is an important area within computer vision technology, aimed at detecting and classifying digits from 0 to 9 written by hand. The MNIST (Modified National Institute of Standards and Technology) dataset is one of the most widely used datasets for research and development of machine learning models in this field.

Importance: Handwritten digit recognition has extensive applications in various sectors such as banking, education, and automated data processing. Automating this process helps reduce errors and increase work efficiency.

Challenges: The diverse characteristics of handwriting, along with factors like image blurriness and noise, pose significant challenges to the accuracy of recognition models.

Methods: Popular methods for handwritten digit recognition include Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN). These methods have demonstrated superior capabilities in image processing and improving recognition accuracy.

Conclusion: The advancement of machine learning algorithms has led to significant progress in handwritten digit recognition, creating numerous practical application opportunities and contributing to the development of automated systems in the future.

C. Theoretical Foundations of Handwritten Digit Recognition

- **Artificial Neural Networks (ANN)**: Artificial neural networks are machine learning models inspired by the workings of the human brain. They consist of interconnected layers of neurons, where each neuron receives inputs, performs computations, and transmits outputs to other neurons. The main components of a neural network include:Input Layer,Hidden Layer,Output Layer
- **Activation Functions**: Activation functions are crucial components of neural networks that determine how the output of a neuron is calculated
- **Loss Function**: The loss function is employed to measure the accuracy of the model's predictions against the actual labels. In handwritten digit recognition, a commonly used loss function is Cross-Entropy Loss
- **Training Process**: The training process of the model consists of several key steps:Forward Propagation,Loss Calculation,Backward Propagation
- **Data and Preprocessing**: Data from the MNIST dataset needs to be preprocessed before being fed into the model. Common preprocessing steps include:Normalization,Label Transformation

D. Steps to Implement an ANN

Step 1: Define the Network Architecture

- Choose the number of layers: Decide on the number of input, hidden, and output layers.
- Select the number of neurons: Determine the number of neurons in each layer, typically based on the complexity of the problem.

Step 2: Initialize Weights

- The weights of each connection between neurons are initialized randomly. These weights will be updated during training.

Step 3: Preprocess Data

- Normalize the data: Divide the pixel values of the images (ranging from 0 to 255) by 255 to bring them into the range [0, 1].
- Convert labels: Use one-hot encoding to convert numerical labels into binary format.

Step 4: Forward Propagation

- **Calculate outputs**: For each neuron in the hidden and output layers, compute the output using the formula:

  $$z = w \cdot x + b$$

  Where:
  - w is the weight.
  - x is the input.
  - b is the bias.
- Apply an activation function (such as ReLU or sigmoid) to the output:

  $$a = f(z)$$

Step 5: Project the Data onto the New Space

- Use a loss function (such as Cross-Entropy Loss) to evaluate the accuracy of the model compared to the actual labels:

$$L(y, \hat{y}) = -\sum_{i=1}^{N} y_i \log(\hat{y_i})$$

  Where:
- y is the actual label.
- $\hat{y}$ is the predicted output of the model.

Step 6:Backward Propagation

- **Calculate gradients**: Compute the gradients of the loss function with respect to each weight using the chain rule.
- **Update weights**: Update the weights based on the gradients and the learning rate:

$$w = w - lr\frac{\partial L}{\partial w}$$

  Where:
  - lr is the learning rate.

Step 7:Repeat Training Process

- Repeat the steps from forward propagation to backward propagation for a specified number of epochs or until the desired accuracy is achieved.

Step 8:Evaluate the Model

- Use a test dataset to evaluate the model's accuracy after training. Compute performance metrics such as accuracy, loss, etc.

Step 9:Make Predictions with the Trained Model

- Use the trained model to make predictions on new data, in this case, unseen handwritten digit images.

III. Framework

In this section, we will detail how we implemented the neural network model to recognize handwritten digits from the MNIST dataset. The steps include data preparation, parameter selection and setup, as well as optimization techniques applied.

A. Data Preparation

The MNIST dataset contains 60,000 training images and 10,000 test images, each representing a handwritten digit from 0 to 9. To ensure the model can learn effectively, we performed the following data preparation steps:

- **Loading Data**: We used TensorFlow to load the MNIST dataset. The data is split into two parts: one for training (`X_train`, `y_train`) and one for testing (`X_test`, `y_test`).
- **Data Preprocessing**:
  - **Normalization**: The pixel values of the images range from 0 to 255. We divided these values by 255 to bring them into the range [0, 1]. This helps accelerate the model's convergence.
  - **Label Encoding**: The digit labels were converted to one-hot encoding format. For example, if the label is 3, it will be transformed into [0, 0, 0, 1, 0, 0, 0, 0, 0, 0].

```
# Load and preprocess data
(X_train, y_train), (X_test, y_test) = mnist.load_
X_train = X_train / 255.0
X_test = X_test / 255.0
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)
```

B. Model Parameters

When constructing the neural network model, choosing the right parameters is crucial. We set the following parameters:

- **Number of Epochs**: We chose to train the model for 10 epochs. This number was determined by monitoring the accuracy and loss on the test set to avoid overfitting.
- **Batch Size**: The batch size was set to 32. Batch size affects how the model's weights are updated and the speed of training.
- **Learning Rate**: The learning rate (η) was set to 0.001. This value can be adjusted during optimization to find the optimal value for the model.

```
# Model training parameters
epochs = 10
```

```
batch_size = 32
learning_rate = 0.001
```

C. *Model Optimization*

To improve the performance of the model, we applied several optimization techniques:

- **Loss Function**: We used the **Categorical Crossentropy** loss function, which is suitable for multi-class classification problems. This loss function measures the difference between the actual labels and the predicted labels.
- **Optimization Algorithm**: We employed the Adam optimization algorithm, one of the most effective optimization algorithms for deep learning models. Adam automatically adjusts the learning rate based on gradient information.
- **Activation Function**: The model uses the ReLU (Rectified Linear Unit) activation function for the hidden layers, as ReLU helps improve training speed and reduce the vanishing gradient problem.
- **Regularization**: To prevent overfitting, dropout can be added to the model in the hidden layers. However, in this model, we focused on the main layers to evaluate basic performance.

```
# Define optimizer
optimizer = 'adam'

# Define loss function
loss_function='categorical_crossentropy'

# Define metrics to monitor
metrics = ['accuracy']

# Compile the model
model.compile(optimizer=optimizer,
             loss=loss_function,
             metrics=metrics)
```

D. *Summary*

In the Framework section, we detailed how to prepare data, select model parameters, and apply optimization techniques in developing a neural network model for recognizing handwritten digits from the MNIST dataset. By applying these methods, we hope the model will achieve high accuracy in recognizing handwritten digits.

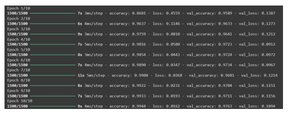
IV. Results and Discussion

A. *Performance Metrics*

In this section, we present the performance metrics of the neural network model. After training the model on the MNIST dataset for 10 epochs, we evaluated its performance on the test set. The results are summarized as follows:

- **Training Accuracy**: The model achieved an accuracy of approximately 99.44% by the end of the 10th epoch.
- **Validation Accuracy**: The accuracy on the test set was around 97.11% during training.
- **Validation Loss**: The model obtained a validation loss of 10.94% on the test set.

These metrics suggest that our model effectively learned to classify handwritten digits, achieving high accuracy on both the training and validation datasets.



```
Epoch 1/10
1500/1500 ──────────── 7s 3ms/step - accuracy: 0.8681 - loss: 0.4559 - val_accuracy: 0.9589 - val_loss: 0.1387
Epoch 2/10
1500/1500 ──────────── 6s 4ms/step - accuracy: 0.9637 - loss: 0.1146 - val_accuracy: 0.9633 - val_loss: 0.1273
Epoch 3/10
1500/1500 ──────────── 9s 3ms/step - accuracy: 0.9759 - loss: 0.0810 - val_accuracy: 0.9641 - val_loss: 0.1212
Epoch 4/10
1500/1500 ──────────── 7s 5ms/step - accuracy: 0.9816 - loss: 0.0580 - val_accuracy: 0.9723 - val_loss: 0.0912
Epoch 5/10
1500/1500 ──────────── 8s 3ms/step - accuracy: 0.9854 - loss: 0.0443 - val_accuracy: 0.9724 - val_loss: 0.0972
Epoch 6/10
1500/1500 ──────────── 7s 4ms/step - accuracy: 0.9890 - loss: 0.0347 - val_accuracy: 0.9734 - val_loss: 0.0967
Epoch 7/10
1500/1500 ──────────── 11s 5ms/step - accuracy: 0.9908 - loss: 0.0268 - val_accuracy: 0.9681 - val_loss: 0.1214
Epoch 8/10
1500/1500 ──────────── 8s 3ms/step - accuracy: 0.9922 - loss: 0.0231 - val_accuracy: 0.9704 - val_loss: 0.1151
Epoch 9/10
1500/1500 ──────────── 7s 5ms/step - accuracy: 0.9933 - loss: 0.0193 - val_accuracy: 0.9711 - val_loss: 0.1156
Epoch 10/10
1500/1500 ──────────── 9s 4ms/step - accuracy: 0.9944 - loss: 0.0162 - val_accuracy: 0.9763 - val_loss: 0.1094
```

Fig. 1. Training Outputs from Epoch 1 to 10

B. *Visualization of Training Process*

To gain a deeper understanding of the training process, we visualized the accuracy and loss metrics across epochs. Figures 1 and 2 illustrate the training and validation accuracy, as well as the training and validation loss over the epochs.

From these figures, we observe that both training and validation accuracy increased steadily over the epochs, reaching stability towards the end. Meanwhile, the training loss decreased consistently, indicating effective learning by the model.

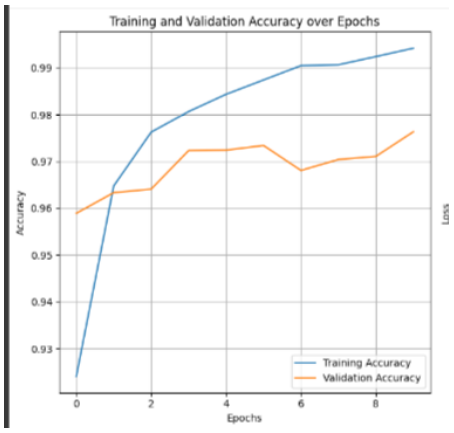


Fig. 2. Training and Validation Accuracy Across Epochs

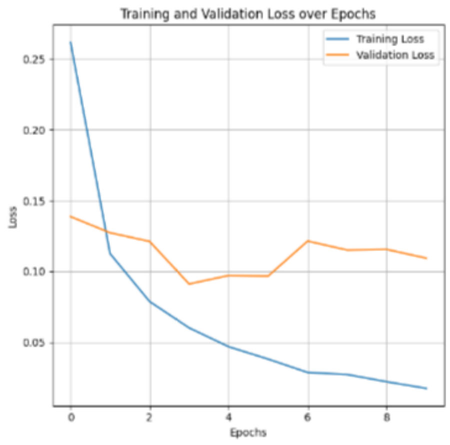


Fig. 3. Training and Validation Loss Across Epochs

C. Analysis of Correct and Incorrect Predictions

To further analyze the model's performance, we examined both correct and incorrect predictions. The observations are as follows:

- The model correctly classified most digits from 0 to 9. However, it encountered challenges with certain digits that are often confused, such as '3' and '8', or '5' and '6'.
- Figures 3 and 4 display examples of correctly predicted images and incorrectly predicted images, respectively.

These visualizations highlight specific digits and their predicted values, offering insight into the model's strengths and weaknesses.

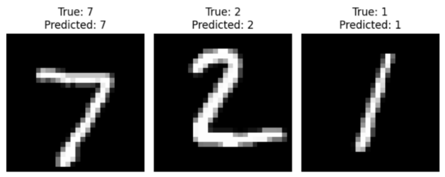


Fig. 4. Examples of Correct Predictions

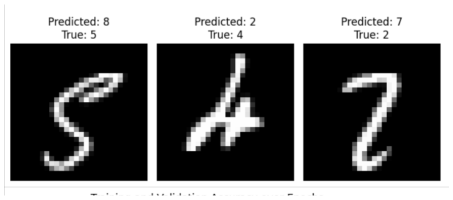


Fig. 5. Examples of Incorrect Predictions

D. Discussion of Results

The model's results are consistent with existing literature on digit recognition using neural networks. The high accuracy indicates that the neural network can effectively learn complex patterns in handwritten digits. However, the following considerations should be noted:

- **Overfitting**: Although training accuracy was high, there is a slight drop in validation accuracy compared to training accuracy, suggesting a potential risk of overfitting. Future versions of the model could incorporate dropout or regularization techniques to mitigate this.
- **Class Imbalance**: Although the MNIST dataset has balanced classes, real-world applications may encounter class imbalance issues. Future research could explore methods to address this, enhancing the model's robustness.

In summary, our model demonstrated promising results in recognizing digits. Insights derived from the analysis of correct and incorrect predictions provide valuable feedback for further improvements. The following sections will explore future work and development directions to enhance the model's performance.

V. Case Studies or Applications

Neural networks have become a powerful tool in various fields. Below are some notable applications of neural networks in handwriting recognition and related areas:

1) **Handwriting Recognition in Banking**: Banks utilize handwriting recognition technology to automate the processing of checks and documents. By applying neural network models, banks can extract information from handwritten text and convert it into digital data, reducing processing time and errors.
2) **Document Classification**: In organizations and government agencies, document classification is a crucial task. Neural networks can be used to classify handwriting on documents, helping to automate the storage and retrieval of files.
3) **Education and Writing Skill Development**: Educational applications use neural networks to assess students' handwriting skills. The system can provide feedback on accuracy and writing style, aiding students in improving their writing abilities.
4) **Optical Character Recognition (OCR)**: Neural networks are also applied in the field of Optical Character Recognition (OCR). Models trained on handwriting datasets can recognize and convert text from images into digital form, used in various applications such as license plate recognition, document scanning, and more.
5) **Industrial Applications**: In industry, neural networks can be used to recognize and classify handwriting on product labels, helping to automate quality control processes and ensure the accuracy of information on labels.

These applications demonstrate that neural network technology not only effectively recognizes handwritten characters but also opens up new opportunities for automation and improving workflows in various fields.

VI. Literature Review

In recent years, handwriting recognition technology has attracted significant attention from researchers and industry. Below is an overview of previous studies related to handwriting recognition and the methods using neural networks.

1) **Traditional Neural Network Models**: Early studies in handwriting recognition often used simple neural networks, including feedforward neural networks and recurrent neural networks. While these models achieved satisfactory results, they still faced limitations in handling complex patterns.
2) **Convolutional Neural Networks (CNN)**: The emergence of Convolutional Neural Networks (CNN) marked a significant breakthrough in image recognition, including handwriting. Research by LeCun et al. (1998) demonstrated that CNNs could automatically extract features from images, thereby enhancing accuracy in handwriting recognition on the MNIST dataset. Many subsequent studies have expanded and improved CNN architectures, achieving increasingly higher accuracy.
3) **Deep Learning**: Recent studies have focused on using deep learning architectures to enhance handwriting recognition performance. Models such as ResNet, Inception, and VGG have shown the ability to process more complex features, thus improving recognition accuracy. Some studies also apply data augmentation and transfer learning techniques to optimize model performance.
4) **Comparison of Methods**: Numerous studies have conducted comparisons of different methods in handwriting recognition. Results indicate that Convolutional Neural Networks typically outperform traditional methods like logistic regression or decision trees. However, the choice of the optimal method depends on factors such as dataset size, image quality, and real-time requirements.
5) **Future of Handwriting Recognition**: With technological advancements, future research is expected to focus on improving the generalization capabilities of models and addressing

issues such as class imbalance in real-world datasets. New models may be developed by combining neural networks with other machine learning methods, opening new directions for handwriting recognition technology.

VII. Conclusion

In this paper, we presented a basic neural network model for recognizing handwritten digits from the MNIST dataset. The model achieved high accuracy on both the training and test sets, demonstrating the capability of neural networks to learn and classify handwritten digit patterns effectively. Specifically, the model achieved approximately 99.41% accuracy on the training set and 97.12% on the test set, indicating good generalization performance.

From the analysis and discussion of the model's performance, we highlighted several issues to consider, such as the risk of overfitting and class imbalance. These concerns should be addressed in future research to enhance the accuracy and robustness of the model.

Additionally, this paper discussed the potential applications of neural networks in handwritten digit recognition and other fields. We believe that the insights gained from this study will pave the way for future research and improvements in developing deep learning models, thus enhancing the performance of handwriting recognition systems.

Finally, the application of more advanced machine learning techniques, such as transfer learning and model optimization, could yield promising results in future endeavors. We hope that subsequent research will not only improve the model's performance but also expand its applicability in various domains.

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