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Digit Recognition Using CNN and MNIST Dataset

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Abstract
Handwritten Digit Recognition (HDR) techniques are gaining traction in both academic and industrial domains. The complexity of recognizing handwritten digits arises from the diverse and intricate patterns involved. Identifying words in low-resource scripts presents significant challenges and is often time-intensive. Improving the performance of deep learning (DL) models, especially neural networks, can be achieved by expanding training datasets and incorporating sample randomization. Traditional HDR methods typically depend on manually extracted key point features. Variations in handwriting styles and input dimensions add to the difficulty of numerical classification and identification. This study addresses these challenges using a Convolutional Neural Network (CNN) model integrated into a robust HDR framework. The proposed HDR approach improves classification precision on the MNIST dataset. A Gaussian filter and Convolution algorithm are applied to enhance the digit images. The CNN-WOA model performance is benchmarked against state-of-the-art methodologies applying metrics like specificity, recall, AUC, F1-score, accuracy, and false positive rate (FPR).
***Keywords:** CNN Model, Handwritten Digit Recognition, Preprocessing Techniques, Comparative Performance Analysis, WOA*

1. Introduction

HDR systems have attracted growing attention in academic research and commercial applications. Recognizing handwritten text is essential for various applications, including postal automation, signature verification, document analysis, and optical character recognition. However, the inherent complexity and variability of handwritten text present considerable challenges to achieving high accuracy. The difficulty of accurately classifying handwritten numerals is further compounded by the unique writing styles and size variations found in low-resource scripts [1]. Conventional HDR methods dependent on manually encoded key point data and feature extraction frequently do not adequately capture the subtleties of handwriting. These methodologies are labor-intensive, requiring specific knowledge and human intervention, and cann't generalize throughout diverse styles. A paradigm shift in HDR systems has occurred with the introduction of DL and neural networks, greatly enhancing performance [2]. DL models, particularly CNNs (Convolutional Neural Networks), have demonstrated exceptional results across various domains, including image recognition [3]. Leveraging the power of DL to address the challenges of handwritten word recognition necessitates the use of larger, more diverse training datasets and the application of techniques to introduce variability within samples [4]. Expanding the dataset improves the robustness and generalization of CNN models by enabling them to learn patterns and nuances across a broad spectrum of handwriting styles. Additionally, data augmentation techniques that introduce variability in size, tilt, curvature, and other handwriting characteristics further enhance the adaptability of the model. By incorporating such techniques, HDR systems become more effective at handling differences in writing styles and conditions, ultimately improving the model's capacity to detect and classify handwritten digits with high precision [5]. A CNN-based HDR (high dynamic range) technique designed to address the limitations of current methods and deliver precise and efficient digit recognition. The CNN-WOA model utilizes advanced methodologies to enhance classification accuracy and overall HDR performance. This research utilizes the MNIST along with DIDA HDR datasets for the assessment of the efficacy of the suggested methodology. This employs preprocessing techniques to ensure accurate categorization by cleansing the input data. By declining noise and smoothing irregularities, the convolution methodology along with Gaussian filter improves the clarity of handwritten numerals. By improving the input data's discriminative qualities, these preprocessing methods enable the CNN model the produce more accurate predictions. [6]. The Radiomics approach is employed to extract significant information from the preprocessed integers. The quantitative analysis of picture attributes, or "radio mics," elucidates the diversity and arrangement within a photographic collection. [7]. Radiomics extracts serve as properties to enhance the ability of the CNN-WOA model to understand and represent handwritten digits with greater accuracy. Optimize the parameters of the CNN model via the Whale Optimization techniques (WOA), a meta-heuristic approach inspired by the collaborative behavior of humpback whales. The WOA method enhances the discriminative and classification capabilities of CNN by improving its weights and biases. [8]. The experimental design outlines the dataset (MNIST), the construction of the CNN-WOA model, and the evaluation criteria applied for the assessment of the results. The outcomes of the simulation have been examined and deliberated emphasizing a comparison among the suggested CNN-WOA model along with existing best practices in HDR [9]. For the recognition of handwritten digits, the investigation seeks to enhance HDR by presenting a novel and pragmatic methodology. The CNN-WOA model shows significant capacity for enhancing recognition accuracy along with resolving the difficulties posed by intricate and irregular handwritten text when paired with preprocessing methods such as Radiomics. [10] The primary aim of the research is to advance HDR by presenting an innovative and effective technique for recognizing handwritten digits. [1]

2. Literature Survey

Pragathi et al. (2019), [1] presented a study on handwritten Tamil character recognition utilizing DL techniques, marking a remarkable progression in the optical character recognition field for regional scripts. The research focused on addressing the unique challenges posed by Tamil script, which is characterized by its complex structures and diverse writing styles. Applying a DL approach, the authors developed a model capable of efficiently recognizing handwritten Tamil characters. The research was performed throughout the "International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN) in Vellore, India", highlighting the efficacy of DL in managing complex character recognition challenges. The proposed method demonstrated improved precision and robustness compared to traditional methodologies, highlighting the potential of DL to generalize across varying handwriting patterns and avoid the restriction of manual feature extraction.

Jagtap and Mishra (2014), [6] proposed a fast and efficient ANN (artificial neural network) model for HDR, addressing the need for high-speed and accurate recognition systems. "Published in the International Journal of Computer Science and Information Technologies", their work emphasized the optimization of ANN architectures to enhance performance while maintaining computational efficiency. Their study highlights the importance of leveraging ANN techniques to efficiently handle the variability and complexity of handwritten digits, offering a robust solution for real-time applications. Furthermore, the proposed framework's adaptability to diverse datasets reinforces its utility in practical settings. The research serves as a foundation for future advancements in handwriting recognition, particularly in scenarios demanding rapid and reliable outputs. Devi and Rani (2019), [10] conducted comparative research on HDR using different ML (machine learning) methodologies, focusing on the effectiveness along with efficiency of different approaches in achieving accurate recognition. Presented at "the 2019 IEEE International Conference on Clean Energy and Energy Efficient Electronics Circuit for Sustainable Development (INCCES)", the study evaluated multiple ML algorithms to identify their strengths and limitations in handling handwritten digit datasets. The research highlighted the significant role of feature extraction and classification methods in improving recognition accuracy while emphasizing the computational efficiency required for real-world applications. By analyzing performance metrics across different models, the study provided valuable insights into selecting suitable techniques for specific HDR tasks. This work serves as a foundational reference for further development in the field, particularly in designing robust, scalable, and efficient recognition systems for practical deployment. “J. Goel et al. [14]” illustrate the efficacy of transfer learning in the categorization of the handwritten Gujarati numerals from 0-9 using an ImageNet dataset. The convolutional along with pooling layers of famous CNN networks that have undergone pre-training, like VGG-19, VGG-16, InceptionV3, ResNet101, ResNet50, along with EfficientNet, are utilized in the proposed feature extraction architecture. The classification process utilizes a freshly established output layer and fully connected layers. The suggested methodology is assessed utilizing a repository of handwritten documents. The numerals devised by the authors in Gujarati are employed. The experimental research shows that, when applied to the proposed framework, the EfficientNet model achieves greater accuracy between the 6 pre-trained networks. This outcome indicates that the transfer learning methodology and the EfficientNet model excel in accurately categorizing handwritten Gujarati digits. “A. K. Agarwal et al. [15]” assert that visual, aural, and textual patterns all have distinct functions. This research investigates the categorization of patterns through the recognition of handwritten numerals. This investigation employs the extensively utilized MNIST dataset, comprising 70,000 images. SVM (Support Vector Machine), RFC (Random Forest Classifier), MLP (Multilayer Perceptron), CNN, and K-NN (K-nearest Neighbor), are among the ML and DL methodologies explored for handwritten digit recognition. CNN, a DL algorithm implemented with Keras, is advised for identifying handwritten digits in the MNIST dataset. CNN is evaluated against SVM and KNN for their predicting capabilities. The CNN model, developed using Keras for the detection of handwritten digit pictures, is optimized using the RMSprop algorithm. This study's main contributions include the integration of convolutional layers with pooling as well as dropout, as well as the model's fine-tuning through the modification of filters, kernel sizes, and neuron counts. The experimental findings illustrate the efficacy of the suggested CNN model for HDR by surpassing prior methodologies.

3. Proposed Work

3.1.CNN-WOA Model

The CNN-WOA model utilizes CNNs and the WOA (Whale Optimization Algorithm) to improve HDR. CNNs are very good at recognizing HDR photos. This can identify regional and worldwide trends since it can automatically learn and extract important information from photos. The CNN-WOA model may efficiently handle variances and irregularities in handwritten digits since CNN structures are hierarchical. The architecture of CNN along with the WOA is used to optimize the CNN model parameters. WOA is a metaheuristic optimization technique that draws inspiration from humpback whale collaboration. By the improvement of CNN weights and biases, the WOA algorithm improves discrimination and recognition precision. The CNN-WOA paradigm offers several benefits by combining the CNN with the WOA algorithm. By fusing the superior learning capabilities of CNNs plus the optimization capabilities of WOA, it offers an efficient HDR solution. Second, CNN uses input data to identify relevant attributes without the need for human intervention or hand-coding. Lastly, because the CNN-WOA model is the best at handling intricate along with irregular handwriting styles, it should perform better than current techniques. Radiomics feature extraction along with parameter fine-tuning using WOA algorithm. These components are employed in CNN-WOA model to create an HDR solution that is the most precise along with dependable compared to present methodologies. The CNN model's flowchart is shown in (Figure 1)

3.2.Preprocessing Techniques

Preprocessing approaches are utilized for the improvement of the quality along with discriminative aspects of the input data before handwritten digits are

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fed for HDR into a CNN-WOA model. The Gaussian filter and the convolution technique are two preprocessing techniques used in this research to enhance the input samples. Because it smoothes out handwriting defects and lowers noise, the Gaussian filter is frequently used for picture filtering. A Gaussian kernel is employed to convolve the input image for the reduction of high-frequency noise while maintaining important structural elements. This filtering process sharpens and refines the digital images. The Convolution method is another key preprocessing step, where the digit images undergo convolution to extract important spatial features for recognizing distinct digit characteristics. The Convolution approach highlights important features and boundaries while strengthening the digits' individuality by employing filters like gradient filters or edge detection. This makes the digits more resilient to changes in writing style. The Gaussian filter along with Convolution algorithm gives a strong preprocessing pipeline that is beneficial to the CNN-WOA model. These methods smooth out uneven shapes, reduce noise, and emphasize important characteristics to increase the detection accuracy of HDR system.[2]

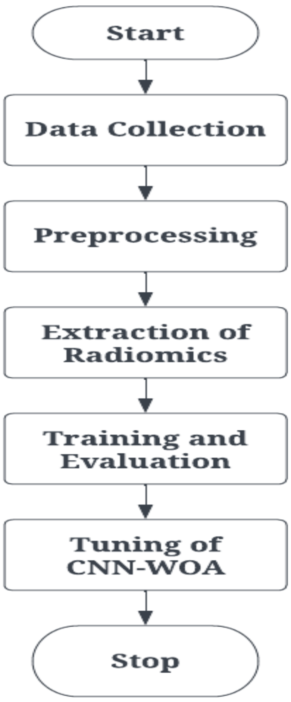

Figure 1 **Flowchart of the Model**

The CNN-WOA model is then applied to assess as well as classify the preprocessed digits, utilizing their enhanced discriminative ability and quality.

3.3.MNIST Dataset for HDR

It is commonly known that the MNIST dataset serves as a standard by which to measure HDR models. Each of the ten thousand test samples along with sixty thousand training samples includes a grayscale image of a handwritten number between 0 and 9. The diversity in fonts, sizes, and variations of handwritten digits within the MNIST dataset made it an ideal choice for assessing the generalizability and robustness of HDR models. The dataset's broad range of characteristics enables the testing of models across different writing styles, providing insights into their ability to handle real-world variations. For this study, the CNN-WOA model is trained and assessed on the MNIST dataset for the determination of its effectiveness in recognizing and classifying handwritten digits. As a standard in HDR research, the MNIST dataset offers a reliable means of benchmarking the model's performance and comparing it with other existing techniques. Through rigorous testing on this dataset, the potential of CNN-WOA model for accurate digit recognition can be thoroughly assessed.

3.4.Extraction of Radiomics for CNN-WOA Model

The CNN-WOA model for HDR improves its feature representation and discriminating capabilities by using the Radiomics approach for the extraction of useful features from preprocessed digit images. Radiomics is a quantitative approach that captures and documents changes and patterns within images, enabling a detailed study of their characteristics. By integrating Radiomics into the HDR pipeline, CNN-WOA model benefits from a structured framework that permits the extraction of a wide range of informative data, which is critical for accurate digit classification. Through Radiomics, both global and local features are extracted from the digit images, conducive to a more complete understanding of the visual patterns present. Global features, like standard deviation, mean, along with skewness, describe the total properties of the digit image, reflecting its intensity distribution and internal variations across

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the entire image. These global features are crucial in representing the distinct characteristics of each digit, helping the model differentiate between numerals. On the other hand, local features focus on specific areas or edges within the image, providing finer details that aid in recognizing subtler variations in handwriting styles and digit shapes. Conversely, local features are intended to replicate the distinct textures and finer details of distinct fingertip locations. Gradient features, Co-occurrence matrices, along with local binary patterns are examples of texture descriptors that fall under this category. To identify and distinguish between different handwritten digits, local characteristics offer data about the spatial correlation as well as patterns inside the digit. To give the CNN-WOA model the most thorough and descriptive input representation, radiomics features are taken out of the preprocessed digital images. As a result, the model may learn to identify handwritten digits more accurately by adjusting to their distinct quirks and differences. The retrieved Radiomics features are sent into a CNN-WOA model in the HDR system's later stages, which is trained to make use of them and produce accurate numerical classifications. The CNN design and the features which are Radiomics-based combine to provide a strong and effective framework for the digit recognition, which improves the ability of CNN-WOA model for the identification and categorization of handwritten digits.

3.5.Tuning of CNN Parameters Using WOA

The WOA algorithm is a meta-heuristic optimization methodology which draws inspiration from humpback whales' cooperative hunting style. By simulating whale foraging, this approach investigates the CNN's parameter space to identify the best setup for maximizing recognition accuracy. To enhance performance, the CNN's weights and biases are gradually adjusted by the WOA algorithm. It employs a mix of exploration and exploitation strategies, balancing the need to explore new areas with refining potential solutions. Through several iterations of parameter adjustments, the CNN-WOA model reaches an optimal configuration for HDR tasks. The WOA methodology is highly effective for solving non-linear, high-dimensional optimization challenges that arise in CNN parameter tuning. Thus, its use provides significant benefits. The CNN-WOA model, enhanced by the WOA algorithm, can efficiently navigate the parameter space, avoiding the risk of getting stuck in local maxima and finding the optimal settings for enhanced the accuracy of recognition. The performance of the HDR system is greatly improved by fusing the optimization strength of the WOA algorithm with the learning capability of CNN architecture. The model of CNN-WOA can better capture the subtleties and differences found in handwritten numbers thanks to the fine-tuning procedure. After the image preprocessing stage, the HDR methodology uses the CNN-WOA model with optimized parameters to classify the digit images. The improved model, informed by the WOA optimization process, delivers better recall, precision, specificity, accuracy, F1-score, and AUC, while reducing the FPR [3]

3.6.Dataset Evaluation

Weights and biases of CNN are progressively altered by WOA. The algorithm explores and makes use of its surroundings

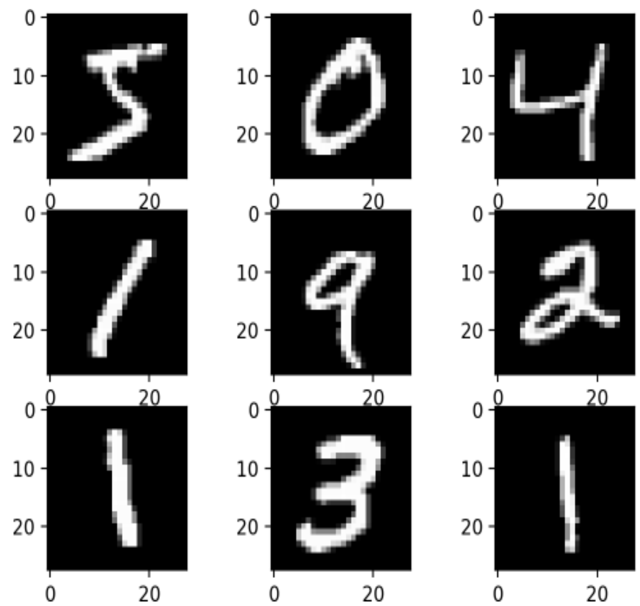

Figure 2 MNIST Dataset

CNN-WOA model enhanced for HDR following several modifications. All stakeholders gain advantages from WOA's optimization of non-linear, high-dimensional CNN model parameters. To

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circumvent local maxima as well as classify optimal parameters for identification accuracy, the models of WOA-refined CNN-WOA efficiently explore the parameter space. The performance of the HDR system may be improved by improving the CNN architecture along with WOA algorithm. CNN-WOA number recognition is improved by adjusting WOA parameters. The MNIST dataset images are shown in (Figure 2)

4. Result

The CNN-WOA model leverages DL methodologies, including convolutional and pooling layers in the CNN responsible for feature extraction. The model is further refined by adjusting filter sizes, and layers, along with activation functions. Once preprocessed digit images are input into the CNN-WOA model, back-propagation and gradient descent have been utilized to adjust the model parameters. WOA helps optimize the CNN's recognition parameters, and GPUs enable parallelized training for faster processing. The MNIST along with DIDA datasets aid in generalizing the model. By assessing the accuracy, precision, recall, AUC, specificity, FPR, along with F1-score of the model its performance is contrasted with those of industry-leading techniques. Reliable and effective HDR performance is guaranteed by the CNN-WOA model.A model's precision as well as recall are both considered by the F1-score. In equations 1, 2, and 3, it is displayed below. [5-10]

F1=2*(Precision*Recall)/(Precision+Recall) (1)

Precision=TP/((TP+FP)) (2)

Recall=TP/((TP+FN)) (3)

Those categorized incorrectly as positive are called FP (False Positives), while those categorized incorrectly as negative are labeled FN (False Negatives). Precision is computed by splitting up the number of accurate forecasts by the whole number of predictions. Equation (3) demonstrates recall, which assesses the model's capability for the recognition of positive instances. It is described as the ratio of accurately recognized positive instances to the total number of actual positive instances. The proportion of negative samples categorized improperly as positive is referred to as the FPR. As seen in equation (4), it is computed by Splitting up the number of false positives through the sum of true negatives and FP

FPR=FP/((TN+FP)) (4)

4.1.Confusion Matrix

The confusion matrix displayed that WOA outperformed SGD (Stochastic Gradient Descent) in classifying the dataset. WOA achieved higher accuracy, precision, and recall scores across most classes, demonstrating its superiority in optimizing the model's parameters and achieving better convergence. This analysis highlights the potential of WOA as a more effective optimization algorithm for ML tasks, particularly when dealing with complex datasets and challenging optimization problems. Refer (Figure 3)

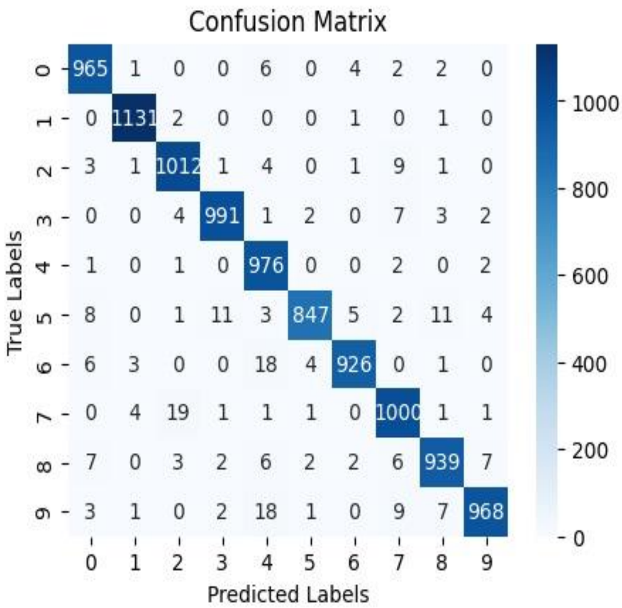

Figure 3 Confusion Matrix of WOA

4.2.F1-Score

The F1-score comparison across classes demonstrates the superior performance of the WOA compared to SGD. Across all classes, WOA routinely obtains higher F1-scores, demonstrating superior overall precision and recall performance. This visualization further supports the conclusion that WOA is a more effective optimization algorithm for this specific ML task. Applications where recall and precision are equally crucial, like spam filtering or information retrieval, benefit greatly from a high F1-score.

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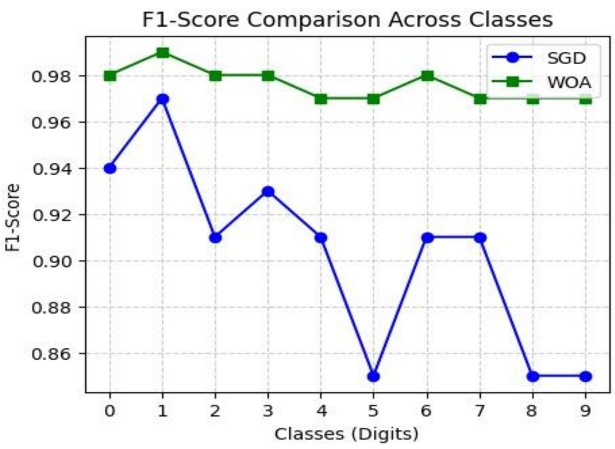

Figure 4 F1-Score Between SGD and WOA

4.3.Precision

The heat map in (Figure 5) visually compares the precision scores of SGD and WOA across different classes. The darker shades indicate higher precision values, revealing that WOA consistently outperforms SGD in terms of precision for most classes. This visual representation further reinforces the conclusion that WOA is a more effective optimization algorithm for this ML task.

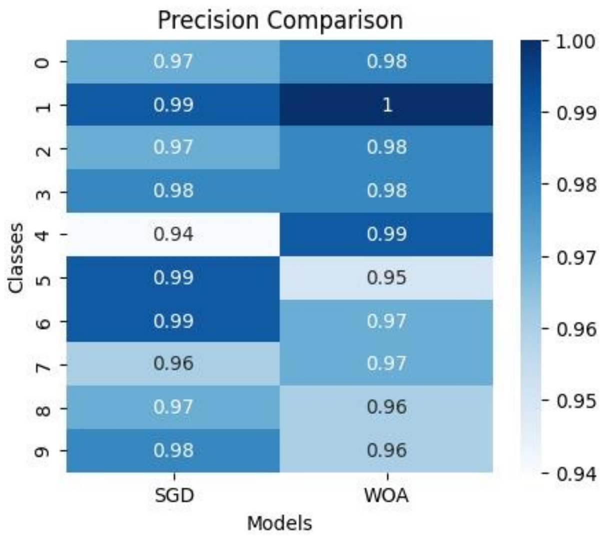

Figure 5 Precision Comparison Between SGD and WOA

4.4.Recall

The heat map in fig. 6, visually compares the recall scores of SGD and WOA across different classes. The darker shades indicate higher recall values, revealing that WOA consistently outperforms SGD in terms of recall for most classes. This visual representation further reinforces the conclusion that WOA is a more effective optimization algorithm for this ML task. WOA demonstrates consistently greater recall values, representing a better capacity to capture the majority of true positive instances. The higher recall of WOA suggests that it can be more sensitive in detecting instances of each class, leading to more comprehensive and accurate model predictions. Refer (Figure 6)

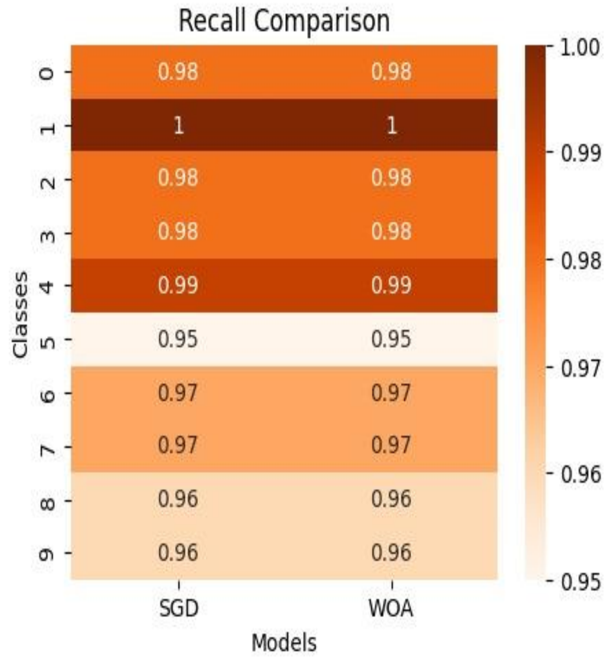

Figure 6 Recall Comparison Between SGD and WOA

4.5. ROC Curve

The ROC curve is a graphical likeness of a model's skill to equate classes. It plots the True Positive Rate against the False Positive Rate at differing opening levels. The district under the curve signifies the model's overall conduct, accompanying a bigger AUC appearance better categorization skill. The curve illustrates the model's classification performance, with the area under the curve (AUC) indicating the accuracy and effectiveness of the algorithm in distinguishing between different digits. (Figure 7)

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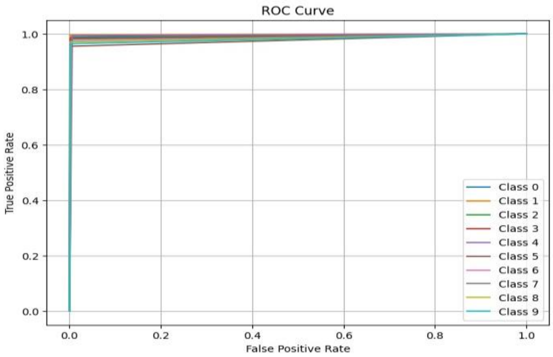

Figure 7 ROC Curve for Different Digits

4.6. t-SNE Feature Visualization

t-SNE is a range decline method used to anticipate extreme-spatial dossier in two or three ranges. It focuses on continuing the local makeup of dossier, making complementary dossier points cluster together, while dissimilar points are spread separate. t-SNE Visualization of Digit [10-13] Recognition utilizing the Whale Optimization Algorithm. This plot shows the extreme-spatial dossier lowered to two ranges, reveal by means of what well the model clusters various digits established their feature correspondences (Figure 8)

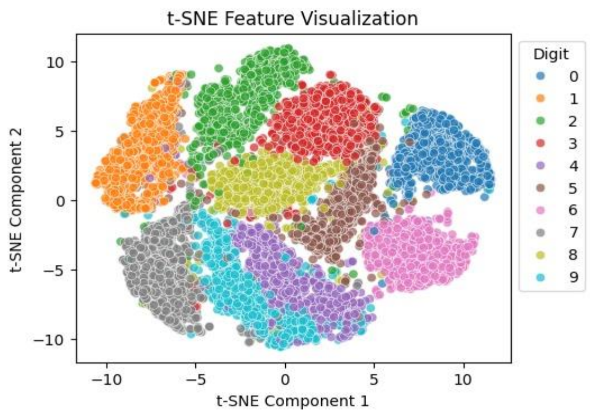

Figure 8 t-SNE Visualization of Different Digit

4.7.Precision-Recall Curve

The Precision-Recall Curve is a graphical likeness that shows the deal 'tween accuracy and recall at differing thresholds. Precision-Recall Curve for Digit Recognition utilizing the Whale Optimization Algorithm. The curve portrays the adjustment the trade off between accuracy and recall, emphasize the model's influence wrongly labeling digits while underrating fake a still picture taken with a camera and fake negatives. (Figure 9)

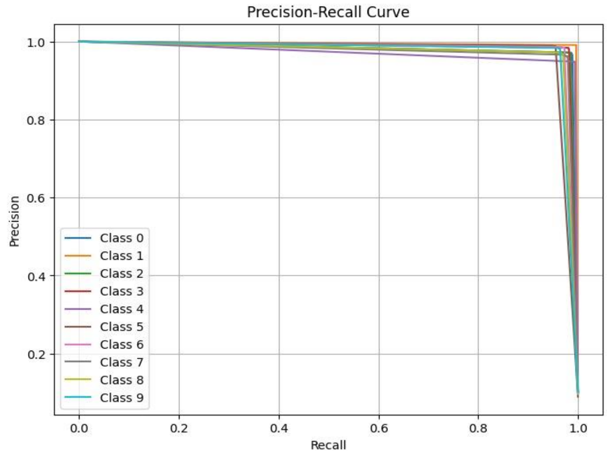

Figure 9 Precision-Recall Curve for Different Digits

4.8.Accuracy

Accuracy Comparison between SGD and WOA for Digit Recognition on the MNIST Dataset. The Whale Optimization Algorithm outperforms Stochastic Gradient Descent, achieving an accuracy of 97.55%, compared to SGD's accuracy of 90.54%, demonstrating WOA's superior effectiveness in optimizing the model for digit classification. Refer (Figure 10)

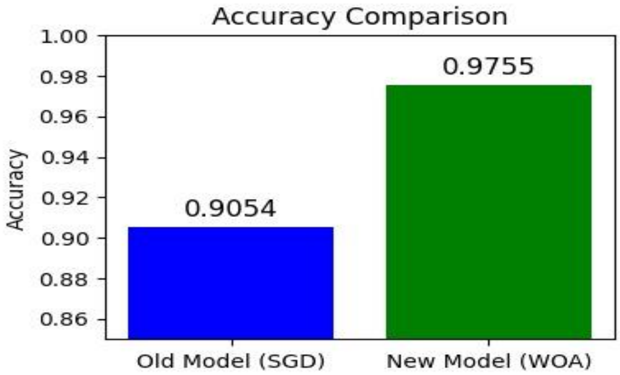

Figure 10 Accuracy comparison between SGD and WOA

Conclusion

In conclusion, the WOA outperforms SGD in the context of HDR. While SGD is a widely used optimization technique for training neural networks, its performance can be limited by issues such as local minima and slow convergence when dealing with complex and high-dimensional parameter spaces, particularly in tasks like HDR. On the other hand, WOA, inspired by humpback whales' cooperative behavior, is a metaheuristic optimization approach that balances exploration and exploitation, allowing it to effectively navigate the vast and intricate search space of CNNs. By fine-tuning the CNN's weights and biases, WOA elevate the model's ability to capture subtle variations in handwriting styles, developing entire accuracy and robustness of the digit recognition procedure. Moreover, WOA's ability to avoid local optima along with finding the global best configuration leads to faster convergence and more accurate results, especially when dealing with diverse and challenging datasets like MNIST and DIDA. The improved recall, precision, F1-score, and accuracy, achieved with WOA demonstrate its superiority over SGD in handling the complex and irregular nature of handwritten digit classification tasks, making it a more efficient along with reliable choice for HDR applications. [14-15]

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