Predicting Early Motor Skill Challenges Through Handwriting Recognition:

A Comparative Study of K-Nearest Neighbors and Neural Network Models

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February 2026

Abstract

Early identification of motor skill development challenges in children can significantly improve educational interventions and long-term academic outcomes. This study investigates whether a handwriting recognition task can be used as an early screening mechanism to identify students who may require additional motor skill support. Using a dataset of handwritten numerical characters, two machine learning approaches were developed and evaluated: a K-Nearest Neighbors (KNN) classifier and a neural network model. The KNN model provides a simple, distance-based baseline, while the neural network captures more complex, non-linear patterns in pixel-level handwriting data. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrices. Results indicate that while KNN offers interpretability and ease of implementation, the neural network significantly outperforms KNN in predictive accuracy and robustness. The findings suggest that neural networks are better suited for deployment in educational screening tools, though KNN remains valuable for exploratory analysis and interpretability.

INTRODUCTION

Motor skill development plays a critical role in early childhood education, influencing handwriting ability, cognitive development, and overall academic performance. Writing tasks, particularly those involving numerical characters, require coordinated fine motor control, spatial awareness, and visual-motor integration. Difficulties in these areas may signal underlying motor development challenges that warrant early intervention.

Schools are increasingly interested in data-driven tools that can assist educators in identifying students who may benefit from additional support. Handwriting recognition offers a promising avenue for such screening, as it allows objective analysis of student-produced artifacts rather than relying solely on subjective observation. If a machine learning model can accurately identify what a student has written, persistent misclassification or low confidence predictions may indicate motor control difficulties rather than conceptual misunderstanding.

This study explores whether predictive modeling techniques can accurately classify handwritten numbers and, by extension, support early identification of students who may need motor skill interventions. Two models are examined: K-Nearest Neighbors (KNN), a simple and interpretable algorithm, and a neural network, a more complex model capable of learning hierarchical feature representations. The central research question is whether the increased complexity of neural networks provides sufficient performance gains to justify their use in an educational screening context.

DATA DESCRIPTION AND PREPROCESSING

The dataset used in this study consists of grayscale images representing handwritten numerical characters. Each observation corresponds to a single handwritten digit, encoded as pixel intensity values flattened into a numerical feature vector. The target variable represents the true digit label drawn by the student.

Before model development, several preprocessing steps were applied to ensure data quality and model compatibility. First, the dataset was inspected for missing or corrupted values. No significant missing data were observed, but all features were validated to ensure numeric consistency. Pixel values were normalized to a standard scale to prevent features with larger numerical ranges from dominating distance-based calculations, particularly important for KNN.

The dataset was then partitioned into training and testing subsets using an 80/20 split. Stratified sampling was applied to preserve class balance across digits, ensuring that each numerical category was proportionally represented in both sets. This step was critical to prevent biased evaluation results caused by uneven class distributions.

Dimensionality reduction techniques were not applied in order to preserve the full spatial information contained in the pixel data. While this increases computational cost, it allows both models to leverage the complete structure of the handwritten images.

PART 1: K-NEAREST NEIGHBORS MODEL

Model Development

K-Nearest Neighbors is a non-parametric, instance-based learning algorithm that classifies observations based on the labels of the closest data points in feature space. For handwriting recognition, KNN compares pixel-level similarity between handwritten samples using a distance metric, typically Euclidean distance.

Multiple values of k were tested to identify the optimal neighborhood size. Smaller values of k increase sensitivity to local variations but are prone to noise, while larger values smooth predictions but may blur class boundaries. Cross-validation revealed that moderate k values produced the best balance between bias and variance.

Model Performance

The KNN model achieved moderate classification accuracy on the test set, correctly identifying a substantial portion of handwritten digits. Performance varied by digit, with clearly distinguishable numbers (such as “0” and “1”) achieving higher accuracy, while visually similar digits (such as “3” and “5”) were more frequently misclassified.

Precision and recall metrics showed uneven performance across classes, indicating that KNN struggles when handwriting styles vary significantly. The confusion matrix revealed that misclassifications often occurred between digits with similar stroke patterns, suggesting limitations in distance-based similarity when handwriting variation is high.

Challenges of KNN

Several challenges emerged when using KNN for handwriting recognition. First, the algorithm is computationally expensive, as it requires distance calculations against the entire training dataset for each prediction. This limitation reduces scalability in real-time educational applications. Second, KNN is highly sensitive to feature scaling and noise, making it vulnerable to inconsistent handwriting styles. Finally, KNN lacks the ability to learn abstract representations, relying solely on raw pixel similarity rather than higher-level shape features.

PART 2: NEURAL NETWORK MODEL

Model Architecture and Training

A feedforward neural network was developed to address the limitations of KNN. The network consisted of an input layer corresponding to pixel features, one or more hidden layers with nonlinear activation functions, and an output layer using softmax activation for multi-class classification.

The neural network was trained using backpropagation and gradient descent optimization. Early stopping and regularization techniques were applied to mitigate overfitting. Training was conducted over multiple epochs, allowing the model to iteratively refine its internal weights based on classification errors.

Model Performance

The neural network significantly outperformed the KNN model across all evaluation metrics. Test accuracy was substantially higher, indicating stronger generalization to unseen handwriting samples. Precision and recall improved consistently across all digit classes, demonstrating the model's ability to distinguish subtle differences in handwriting patterns.

The confusion matrix showed fewer misclassifications between visually similar digits, highlighting the neural network's capacity to learn hierarchical feature representations such as curves, angles, and stroke intersections. These learned representations enable more robust predictions even when handwriting styles vary widely.

Challenges of Neural Networks

Despite superior performance, neural networks introduce their own challenges. Training requires greater computational resources and longer execution time compared to KNN. Additionally, neural networks are less interpretable, making it more difficult to explain individual predictions to educators or administrators. Model tuning—including selecting the number of layers, neurons, and learning rates—also requires technical expertise.

PART 3: MODEL COMPARISON AND RECOMMENDATION

Benchmarking Metrics

Both models were evaluated using multiple benchmarking metrics, including accuracy, precision, recall, F1-score, and confusion matrices. Accuracy provided an overall performance measure, while precision and recall offered insights into classification reliability and error patterns. The F1-score balanced precision and recall, particularly important for multi-class classification problems.

Across all metrics, the neural network consistently outperformed KNN. The performance gap was especially pronounced for digits with high handwriting variability, suggesting that neural networks are better suited for real-world educational data.

Comparative Analysis

KNN's strengths lie in simplicity, interpretability, and ease of implementation. It serves as an effective baseline model and is valuable for exploratory analysis. However, its sensitivity to noise and computational inefficiency limit its practical use in large-scale or real-time screening applications.

The neural network demonstrates superior predictive accuracy, robustness to variation, and scalability. While it requires greater technical investment, its performance advantages make it a more reliable tool for identifying handwriting patterns that may indicate motor skill challenges.

FINAL RECOMMENDATION

Based on the benchmarking results, the neural network model is recommended for deployment in the school's handwriting assessment framework. Its higher accuracy and consistency provide a stronger foundation for identifying students who may benefit from early motor skill intervention. KNN may still be retained as a supplementary tool for validation or instructional demonstrations.

CONCLUSION

This study demonstrates that machine learning models can effectively classify handwritten numerical characters, supporting the feasibility of handwriting-based screening for early motor skill challenges. While KNN offers simplicity and interpretability, its limitations in handling handwriting variability reduce its effectiveness in applied educational settings. Neural networks, despite increased complexity, provide substantially improved performance and reliability.

The findings suggest that schools seeking data-driven screening tools should prioritize neural network-based models while maintaining transparency and ethical oversight. Future research should explore convolutional neural networks (CNNs), longitudinal handwriting analysis, and integration with broader student assessment frameworks to enhance early intervention strategies.

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