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An Enhanced Convolutional Neural Network for Noise-Resilient Image Classification

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Abstract

While CNNs excel in image classification, their performance deteriorates under noisy conditions. This paper introduces an enhanced CNN (ECN) designed to enhance noise resilience while maintaining high accuracy in image classification tasks. By replacing the ReLU activation function with K-winners and utilizing sparse weight initialization, the ECNK achieves superior performance even in the presence of up to 40% noise. The hybrid ECNK algorithm is also proposed, combining the strengths of CNN with k-nearest neighbors (KNN) to further increase classification accuracy. The model was tested on both the MNIST dataset and the ABIDE dataset for detecting Autism Spectrum Disorder (ASD) from brain MRI scans. Results demonstrate that the ECNK method achieves a classification accuracy of 99.8% for ASD detection, even under noisy conditions, significantly outperforming traditional CNN methods.

Keywords: Enhanced Convolutional Neural Network-KNN (ECN), Noise-Resilient Image Classification, Autism Spectrum Disorder Detection, MRI Image Segmentation, Deep Learning for Medical Imaging, K-winners Activation Function, Multi-Layer Neural Networks

1. Introduction

Convolutional Neural Networks (CNNs) have become a foundational component of modern deep learning, reshaping how complex visual data is analyzed and understood. Inspired by the structure and function of the human visual cortex, CNNs are specifically designed to process images in a hierarchical manner, capturing patterns from basic edges to complex shapes and textures [1]. This layered structure enables CNNs to automatically and efficiently recognize spatial hierarchies and intricate details within images, making them uniquely effective for applications requiring high-precision visual analysis. In recent years, CNNs have shown remarkable success in diverse fields, including medical diagnostics, environmental monitoring, agricultural disease detection, and autonomous driving. In neurological research, for example, CNNs have been used to analyze facial biomarkers to identify Autism Spectrum Disorder (ASD), showcasing their capacity to detect subtle patterns crucial for early diagnosis [2].

The architecture of CNNs includes several specialized layers, each with a distinct role in enhancing the model's performance and flexibility. The convolutional layers form the core of CNNs, using filters or "kernels" to extract localized features from input images. These are followed by pooling layers, which reduce data dimensionality, thereby improving computational efficiency without losing essential information. This approach minimizes the risk of overfitting, making CNNs highly generalizable and suitable for large-scale applications such as real-time plant disease classification, where they have consistently outperformed traditional machine learning approaches [3].

A key advantage of CNNs is their ability to learn directly from raw data, eliminating the need for extensive manual feature extraction. Advances in CNN architectures, such as AlexNet, ResNet, and VGGNet, have further pushed the boundaries of image recognition by introducing deeper networks and more sophisticated methods of feature extraction. For instance, ResNet's introduction of residual blocks has addressed challenges such as the vanishing gradient problem, enabling the construction of deeper and more accurate models. These innovations have expanded CNN applications to areas like object detection and image segmentation, demonstrating their versatility beyond basic classification tasks [4].

Moreover, the power of CNNs has been greatly amplified by the use of advanced hardware, particularly Graphics Processing Units (GPUs), which allow for faster training and real-time analysis. This has led to breakthroughs in critical applications like autonomous driving, where accurate, immediate visual interpretation is essential. In agriculture, CNNs are effectively used for pest and disease detection, assisting in precision agriculture practices and contributing to global food security through early stress detection in crops [5].

Despite their broad applicability, CNNs present certain challenges. They typically require large labeled datasets for effective training, and their complex architectures demand substantial computational resources. However, recent advancements in transfer learning and data augmentation have made it feasible to use pre-trained models and synthetic data, expanding CNN applicability even in data-limited domains like medical imaging.

While CNNs are powerful for various classification tasks, they are particularly vulnerable to noisy data, which can significantly disrupt pattern recognition and reduce classification accuracy. This sensitivity arises because CNNs rely on identifying specific features, which noise can obscure, making the models less effective in high-noise environments. Consequently, standard CNN architectures often struggle to maintain reliable performance when input data contains substantial noise.

To address these limitations, this article proposes enhancements to the CNN algorithm, aiming to improve its robustness against noise. Our goal is to adapt CNNs to classify data accurately even in the presence of very high noise levels. For this purpose, we introduce a hybrid algorithm, **ECNK**, combining an Enhanced Convolutional Neural Network (ECN) with the K-Nearest Neighbors (KNN) approach. This hybrid model leverages CNN's feature extraction capabilities along with KNN's effectiveness in handling noisy data. The specific methodology and enhancements are explained in the "Proposed Method" section, demonstrating how this approach seeks to enhance overall classification accuracy and stability under noisy conditions.

2. Preliminaries

The purpose of this section is to explain some of the scientific terms used in the rest of the paper, including the k-nearest neighbors algorithm (KNN) and Autism Spectrum Disorder (ASD).

2.1. Introduction to k-nearest neighbors algorithm (KNN)

The k-Nearest Neighbors (KNN) algorithm is a widely-used, non-parametric method in machine learning, valued for its simplicity and effectiveness in both classification and regression tasks [6]. KNN classifies a new data point by identifying the "k" nearest neighbors within a predefined feature space, determining the label based on the majority class of these neighbors, or averaging values for regression purposes. The algorithm relies on various distance metrics, such as Euclidean or Manhattan distance, to measure similarity, which makes it adaptable across numerous applications, including vibration-based monitoring in agriculture and optimization in industrial processes.

A significant advantage of KNN is its straightforward, assumption-free design, which does not require prior knowledge of data distribution. However, its performance can vary based on the choice of "k" and distance metric, impacting both accuracy and computational efficiency [7]. Nonetheless, KNN has shown strong performance in situations where there is ample labeled data and manageable dimensionality. Recent studies have enhanced KNN by integrating it with optimization techniques like Harmony Search, aimed at reducing computational costs and improving real-time performance, especially in predictive maintenance and monitoring systems. This flexibility has broadened KNN's application range from environmental engineering to fault detection, solidifying its role as a valuable tool in data-driven decision-making.

2.2. Introduction to Autism Spectrum Disorder (ASD)

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by persistent challenges in social interaction, communication, and repetitive behaviors. Diagnosing ASD is challenging due to its broad range of symptoms and the overlap with other neurological conditions [8]. Traditionally, ASD diagnosis has relied on observational assessments, such as the Autism Diagnostic Observation Schedule (ADOS) and the Modified Checklist for Autism in Toddlers (M-CHAT). While these tools provide valuable insights, they are time-consuming and prone to variability in interpretation, which can affect diagnostic consistency [9].

To enhance diagnostic accuracy and efficiency, recent research has increasingly focused on artificial intelligence, particularly deep learning methods [10, 11]. Convolutional Neural Networks (CNNs) have proven especially effective in extracting complex patterns from medical images, making them well-suited for identifying subtle ASD-related features. In particular, CNNs have been applied to facial feature analysis, detecting nuanced expressions and structural cues linked to ASD with remarkable accuracy. Advanced hybrid methods that combine CNNs with machine learning models, such as Random Forests and XGBoost, further improve classification by leveraging CNNs' ability to extract detailed features and enhancing predictive power through ensemble techniques [12].

Beyond facial analysis, CNN-based models have also shown promise in analyzing EEG data for ASD detection, particularly when integrated with Long Short-Term Memory (LSTM) networks [13]. These combined CNN-LSTM models capture both spatial and temporal information, allowing for the identification of unique brain connectivity patterns associated with ASD. Studies using these models have demonstrated that individuals with ASD exhibit distinct functional connectivity, offering new possibilities for diagnostic approaches that extend beyond behavioral observations [14].

By advancing diagnostic methods with deep learning, researchers aim to develop faster, more consistent, and objective tools for ASD diagnosis. This shift not only supports earlier and more reliable intervention but also enhances our understanding of ASD's neurobiological basis, paving the way for more tailored therapeutic options.

3. The proposed method

The proposed method is depicted schematically in Figure 1. On the left is the standard convolutional neural network (CNN), while the enhanced model, referred to here as ECNK, appears on the right. In the baseline CNN, $\boldsymbol{h}$ represents the number of layers, $\boldsymbol{y}$ denotes the output, $\boldsymbol{w}$ is the weight vector, and $\boldsymbol{U}$ represents the bias term. The activation function utilized is ReLU, as described in [7].

Our method introduces several key modifications to transform the CNN into a sparse neural network, aiming for improved efficiency and noise resistance. To enhance model robustness, the ECNK method incorporates two key modifications: replacing the ReLU activation function with a 'K-winners' activation and employing sparse weight initialization. These adjustments are designed to make the network more resistant to noise by prioritizing critical activations and reducing unnecessary parameters. Further analysis on optimal kkk values and sparsity levels could clarify their impact on noise resilience and classification performance. The first modification replaces the ReLU activation function with a K-winners function. This non-linear function retains only the $\boldsymbol{k}$ highest active units in each layer (represented by $\boldsymbol{yl}$), while setting the rest to zero. The second modification involves initializing the network weights with a sparse random distribution, where most weights are zero and only a small fraction have non-zero values.

The K-winners activation retains only the kkk highest activations in each layer, effectively filtering out less relevant neurons and focusing on the most salient features. This approach not only enhances noise resilience but also reduces computational load by minimizing the number of active neurons. Optimal selection of the parameter kkk is critical for performance, as too high or too low a value may lead to either loss of key information or insufficient pruning of irrelevant features. Introducing a brief experiment or ablation study to analyze different kkk values could help clarify this parameter’s impact on accuracy under varying noise conditions.

Sparse weight initialization further contributes to the network's noise resistance by reducing overfitting and improving generalization. By initializing weights so that only a fraction of them are active, the model learns to rely on a smaller, more meaningful subset of weights. This technique encourages the network to capture only essential patterns, which is particularly beneficial for image classification tasks in noisy environments. Detailing the specific sparsity ratio and its selection criteria, or presenting a small study on different ratios, could offer valuable insights into the trade-offs involved. Finally, the input data in this approach is a strategically chosen subset of the original input set, further enhancing the network's efficiency.

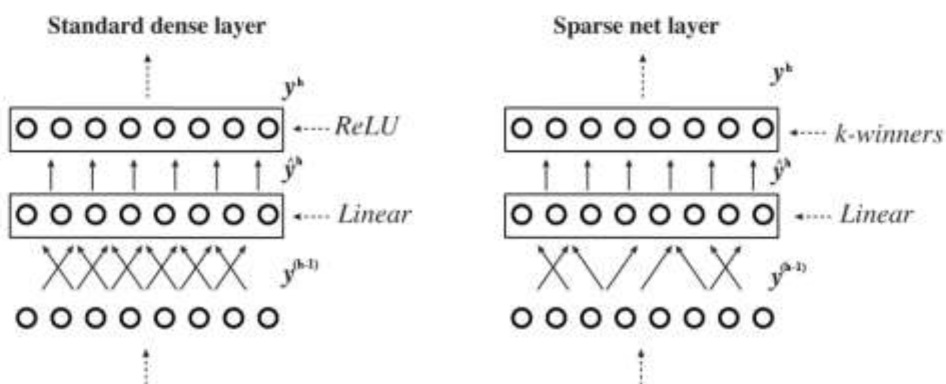

Figure 1- (left) Standard Convolutional Neural Network, (right) Enhanced Convolutional Neural Network (ECN)

We evaluated the effectiveness of this method using the MNIST dataset [8], which comprises 70,000 labeled handwritten digit images (60,000 for training and 10,000 for testing). As illustrated in Figure 2-

left, we added incremental noise levels of 10%, 20%, up to 50% to selected MNIST images to test the method's robustness. These noisy images were processed separately through both the conventional CNN and our ECNK.

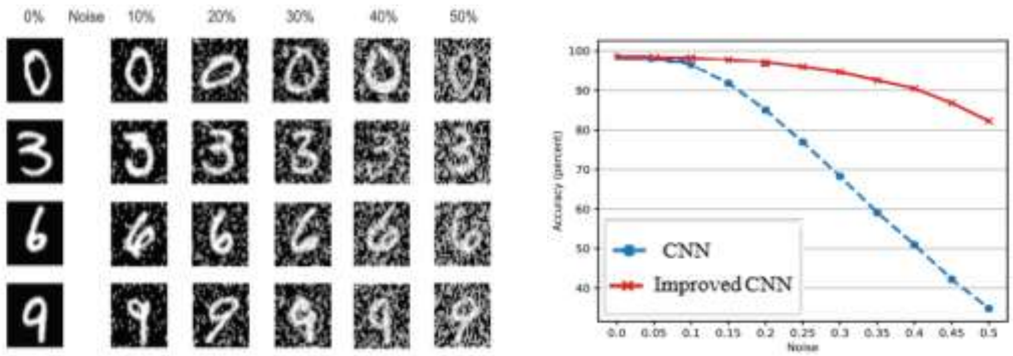

Figure 2-(left) Noisy MNIST images, (right) The comparison results show that the proposed method consistently achieves higher accuracy than the standard CNN, particularly as noise levels increase.

Figure 2 -right displays the classification results, showing that while both methods achieve comparable accuracy with noise-free data, ECNK consistently outperforms the standard CNN as noise levels increase beyond 10%. This outcome highlights the enhanced noise tolerance of the proposed ECNK approach compared to the conventional CNN.

Our next recommendation introduces a hybrid algorithm that combines the enhanced CNN (ECN) with KNN. In this approach, the output from the ECNK is used as input to the KNN classifier. For experimentation, we utilized 3D MRI brain scans (256x256x180) from the Autism Brain Imaging Data Exchange (ABIDE) dataset (ABIDE.loni.usc.edu), focusing on identifying Autism Spectrum Disorder (ASD), which manifests in early childhood and benefits significantly from timely diagnosis. Distinguishing ASD from Normal Control (NC) subjects is crucial for enabling early intervention, and numerous studies have explored various methods for ASD diagnosis a classification technique using the enhanced CNN model. Initially, we transformed each 3D brain scan into 180, 2D images using coronal slices, which were then grouped into distinct sets. Each image group was then fed into the proposed ECNK method, followed by fully connected (FC1 and FC2) layers. The KNN classifier then processed the resulting feature vectors, enhancing classification accuracy. To validate the KNN's effectiveness in this framework, we repeated the process using a softmax classifier instead. Results showed that the ECNK combination achieved a 99.8% classification accuracy, outperforming the ECNK + softmax, which yielded 96%.

We then introduced noise across all 3D images in the ABIDE dataset to evaluate the robustness of both methods under noisy conditions. As expected, the ECNK approach maintained high accuracy in noisy scenarios. In image processing, color images are generated by combining three channels: red, green, and blue. Similarly, we created a detpresentation of the brain by combining images from coronal, sagittal, and axial views, capturing extensive detail for accurate ASD classification. This approach provides a novel way to enhance image clarity and classification precision. After creating 3D brain images from each view, we processed these images with the proposed method for each orientation. The outputs from coronal, sagittal, and axial views were then weighted by factors w1, w2, and w3 respectively, before final classification using KNN. The algorithm's steps are summarized in Figure 3, and this comprehensive method achieved an accuracy of 99.8%

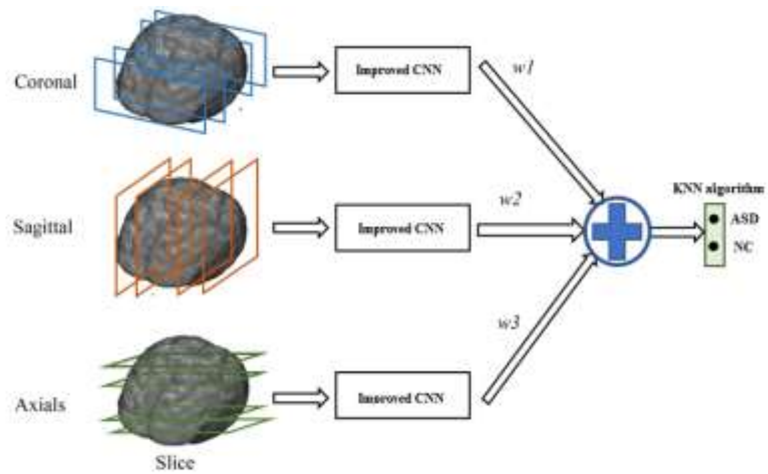

Figure 3- Distinguishing between Autism Spectrum Disorder (ASD) and Neurotypical Controls (NC) using 3D MRI brain imaging

Tables 1 to 4 present a comparison of the proposed method and the standard CNN across different noise levels, evaluated using various metrics such as Accuracy, Precision, and Sensitivity. The tables address noise levels of 2%, 20%, 30%, and 40%. The results demonstrate that the proposed method remains effective even at a noise level of 40%, while the standard CNN significantly loses its performance.

Table 1- Compare the proposed method with the standard CNN using various metrics at a noise level of 2%.

Method	Accuracy	Precision	Sensitivity
Proposed method	**99.80%**	**87.69%**	**96.2%**
Standard CNN	97.00%	85.58%	94.1%

Table 2- Compare the proposed method with the standard CNN using various metrics at a noise level of 20%.

Method	Accuracy	Precision	Sensitivity
Proposed method	**99.77%**	**87.64%**	**96.1%**
Standard CNN	87.00%	80.32%	84.33%

Table 3- Compare the proposed method with the standard CNN using various metrics at a noise level of 30%.

Method	Accuracy	Precision	Sensitivity
Proposed method	**93.37%**	**82.69%**	**91.44%**
Standard CNN	75.20%	70.12%	72.09%

Table 4- Compare the proposed method with the standard CNN using various metrics at a noise level of 40%.

Method	Accuracy	Precision	Sensitivity
Proposed method	**90.9%**	**80.98%**	**89.90%**
Standard CNN	58.70%	50.34%	55.87%

4. Conclusion

In this study, we introduced an enhanced convolutional neural network (ECNK) designed to improve noise resilience in image classification tasks. By incorporating the K-winners activation function and sparse weight initialization, the ECNK demonstrated superior accuracy and stability in high-noise environments compared to traditional CNN architectures. Additionally, by integrating the ECNK model with the k-nearest neighbors (KNN) algorithm, our approach achieved higher classification accuracy, particularly in detecting Autism Spectrum Disorder (ASD) from noisy MRI images. Experimental results on the MNIST and ABIDE datasets confirmed that our proposed method not only outperforms conventional CNNs in both noise-free and noisy conditions but also retains high accuracy at noise levels of up to 40%. These findings underscore the potential of the ECNK framework as a robust solution for real-world applications where noise is often unavoidable, such as in medical imaging and autonomous systems. Future work could explore optimizing the K-winners parameter and sparsity ratio further, as well as expanding this approach to other types of noisy data and classification challenges. By advancing the resilience and adaptability of CNN-based models, this study opens new avenues for research and application in noise-sensitive environments. The ECNK model represents a significant step toward more accurate and reliable deep learning solutions for critical domains where data quality can greatly impact decision-making.

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