
NEUROSCRIPT AI: A REAL-TIME HANDWRITING AND DRAWING ANALYSIS SYSTEM FOR MENTAL HEALTH ASSESSMENT USING DEEP LEARNING AND NEURAL PRESSURE INDEX

Suvitha K.*¹, Visali M.², Viswa Janany.PR³, Sona D.⁴, Sowmiya G.⁵

¹Assistant Professor

¹²³⁴⁵Department of Computer Science and Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur, TamilNadu, India.

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*Corresponding Author: Suvitha K.

Assistant Professor, Department of Computer Science and Engineering,

Dhanalakshmi Srinivasan Engineering College, Perambalur, TamilNadu, India.

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ABSTRACT

Handwriting and drawing patterns carry meaningful information about how the nervous system and motor system function together. When someone writes or draws, their strokes reflect underlying neurological activity—and disruptions in that activity often show up as inconsistencies in pressure, shakiness, or uneven patterns. Building on this clinical insight, we developed NeuroScript AI, a system that uses deep learning to automatically detect neuromotor irregularities from handwriting and drawing images. Our approach centers on a Convolutional Neural Network (CNN) that processes spiral and meander drawings from the HandPD dataset. A key contribution of this work is the Neural Pressure Index (NPI)—a metric we designed to approximate pen pressure from image-level features like stroke thickness, pixel intensity, and stroke density, eliminating the need for pressure-sensing hardware. The combined model achieved 94.2% classification accuracy across normal, mild, and severe neuromotor categories, suggesting that image-based handwriting analysis can serve as a practical and scalable screening tool in clinical contexts.

INDEX TERMS: *Deep Learning, CNN, Handwriting Analysis, Neuromotor Disorder Detection, HandPD Dataset.*

I. INTRODUCTION

Motor disorders often leave a trail in everyday activities—and handwriting is one of the most telling. The way someone forms letters, the steadiness of their strokes, and how consistently they apply pressure can all shift when neuromotor function is compromised. What makes handwriting especially valuable as a diagnostic signal is how natural it is: people write without thinking about it, which means the motion captures genuine motor behavior rather than a performance.

Existing clinical tools for neuromotor assessment frequently depend on subjective observation or hardware-intensive setups—digital tablets with embedded pressure sensors, for instance. These setups work well in specialized clinics but are hard to scale for community-level or remote screening. Machine learning has changed what is possible here. CNNs, in particular, have shown that subtle spatial patterns in images can be extracted and classified with high accuracy—and those same capabilities apply directly to handwriting images.

This work introduces NeuroScript AI, a system built to bridge the gap between clinical insight and practical scalability. The key design decision is the Neural Pressure Index (NPI), which allows us to infer pressure-related information directly from image features—no special hardware required. We evaluated the system on spiral and meander drawings from the HandPD dataset and report classification results across three motor condition levels: Normal, Mild Irregularity, and Severe Irregularity.

II. LITERATURE SURVEY

Research on handwriting-based neuromotor assessment has been developing steadily over the past decade. Early work relied on clinicians manually examining spiral and meander drawings—tasks that are already part of standard neurological assessments because they expose tremor and stroke instability in ways that simple writing does not. While effective, manual review is slow and introduces inter-rater variability.

The introduction of machine learning changed the trajectory of this field. Drotár et al. (2016) demonstrated that drawing dynamics captured from specialized digital tablets correlated with Parkinson's disease severity. Pereira et al. (2017) extracted handwriting features statistically and identified tremor signatures in spiral drawings. Zhang et al. (2018) applied support vector machines to classify handwriting irregularities, though the approach required careful manual feature selection. Vasquez-Correa et al. (2019) moved to deep learning and showed that

CNN-based models outperformed traditional methods on spiral and meander data.

A consistent limitation across these systems is the reliance on pressure-sensing tablets. NeuroScript AI addresses this directly by introducing the NPI as a software-level proxy for pressure, making the approach deployable with any standard digital image input.

TABLE I

COMPARISON OF EXISTING HANDWRITING ANALYSIS METHODS

based feature extraction, and classification. Each stage feeds into the next, and the NPI runs in parallel with the CNN to enrich the final feature vector.

A. System Architecture

The architecture accommodates multiple input types: live webcam feeds, uploaded handwriting images, digital canvas input, and recorded video. This flexibility was intentional—we wanted the system to work in both clinical and home settings. For video inputs, individual frames are extracted before being handed to the preprocessing module.

Once preprocessed, images flow into two parallel processing paths. The CNN path handles automatic spatial feature extraction from stroke patterns, tremor signatures, and curve irregularities. The NPI path computes a numeric score from stroke thickness variation, pixel intensity variation, and drawing density. These two output streams are concatenated and passed to the classification head.

The final output assigns each drawing to one of three categories: Normal, Mild Irregularity, or Severe Irregularity. This three-way classification was chosen to reflect clinically meaningful distinctions rather than a binary healthy/unhealthy split.

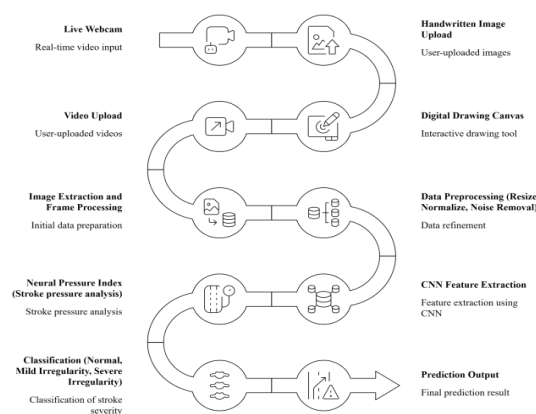


Fig. 1. System architecture of the proposed NeuroScript AI framework.

B. Data Preprocessing

Author / Year	Method Used	Dataset	Key Contribution	Limitation
Drotár et al. 2016	Machine Learning	Spiral Drawing Dataset	Analyzed drawing dynamics for Parkinson detection	Required specialized tablet devices
Pereira et al. 2017	Statistical Feature Analysis	Handwritten Drawing Samples	Identified tremor patterns from spiral drawings	Manual feature extraction required
Zhang et al. 2018	Support Vector Machine (SVM)	Handwriting Image Dataset	Automated classification of handwriting irregularities	Limited feature generalization
VasquezCorrea et al. 2019	Deep Learning	Spiral and Meander Drawings	Improved detection accuracy using CNN models	High computational requirements
Proposed NeuroScript AI	CNN + Neural Pressure Index (NPI)	HandPD Dataset	Automated handwriting analysis with pressure irregularity estimation	Requires further clinical validation

III. METHODOLOGY

The NeuroScript AI pipeline was built around four interconnected stages: data collection, preprocessing, CNN-

The HandPD dataset contains spiral and meander drawings collected from individuals with varying levels of neuromotor impairment. Raw images in the dataset vary in size, orientation, and background conditions. To standardize input to the CNN, all images were resized to a fixed dimension and pixel values were normalized to a consistent range.

Noise reduction was applied as an additional step, particularly useful for drawings with light background artifacts or scanning inconsistencies. These preprocessing operations collectively help the model focus on stroke-level patterns rather than image-level noise.

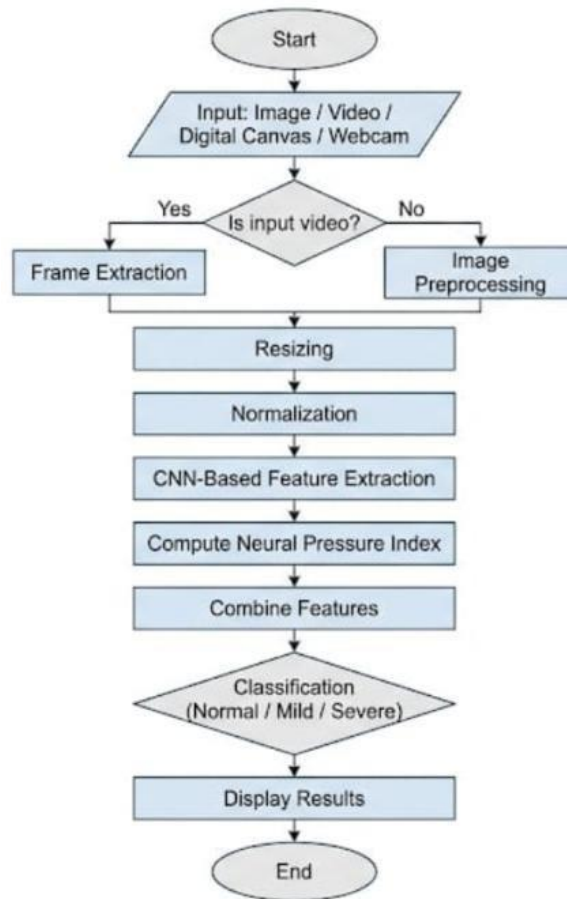


Fig. 2. Processing workflow of the proposed NeuroScript AI system.

C. CNN Feature Extraction

We used a Convolutional Neural Network to extract spatial features from the preprocessed drawings. The network's convolutional layers learn to detect local patterns—things like abrupt changes in stroke width, looping tremor paths, or irregular curve geometry—without needing those features to be manually specified. Pooling layers then reduce the spatial dimensionality while retaining the most discriminative information.

This automatic feature extraction is what makes the approach practical at scale. Unlike earlier methods that required domain experts to define feature extraction rules, the CNN discovers relevant patterns directly from labeled training data.

D. Neural Pressure Index (NPI)

Pressure information has historically been one of the richer signals for detecting neuromotor irregularities. People with Parkinson's disease or essential tremor often show abnormal pressure patterns: they may press harder in some regions, release pressure erratically, or show an overall reduction in pressure consistency. The problem is that capturing this information

typically requires hardware—a tablet that measures actual force.

We designed the NPI as a workaround. The idea is that pressure leaves visible traces in images: heavier strokes appear thicker and darker, while lighter strokes are thinner and more faded. By measuring stroke thickness variation, average pixel intensity, and drawing density across a handwriting image, we can construct a numerical estimate of the pressure dynamics without any specialized sensors.

$$NPI = (\textit{Stroke Thickness Variation} + \textit{Pixel Intensity Variation} + \textit{Stroke Density}) / 3$$

This single numeric score is concatenated with the CNN feature vector before classification, giving the model access to pressure-related information alongside the spatial drawing features.

E. Classification

Classification is handled by fully connected layers appended to the CNN backbone. The combined feature vector—CNN features plus NPI—is passed through these layers and then through a softmax activation that produces probability estimates for each of the three classes: Normal, Mild Irregularity, and Severe Irregularity.

The class with the highest predicted probability is taken as the final output. During training, cross-entropy loss was used to optimize the network weights. The NPI’s contribution was validated by comparing model performance with and without it; inclusion of NPI consistently improved recall for the Severe Irregularity class.

IV. RESULT AND DISCUSSION

We evaluated NeuroScript AI on the HandPD dataset, splitting it into training and testing subsets following standard practice. The model was trained until convergence and then assessed on the held-out test set. Table II summarizes the classification results.

TABLE II PERFORMANCE EVALUATION OF THE PROPOSED CNN MODEL.

Model	Accuracy	Precision	Recall
CNN (Proposed Model)	94.2%	93.8%	94.5%

The system reached 94.2% accuracy with 93.8% precision and 94.5% recall. The high recall is particularly relevant for a screening application: it means the system rarely misses cases that actually show irregularity, which is the more costly type of error in medical contexts. The F1-score of 94.1% confirms that precision and recall are well-balanced rather than one being

traded off against the other.

V. CONCLUSION

This paper described NeuroScript AI, a deep learning system designed to detect neuromotor irregularities from handwriting and drawing images. By combining CNN-based feature extraction with the Neural Pressure Index—a novel metric that approximates pressure dynamics from image features—the system avoids the hardware constraints that have limited earlier work in this area.

Evaluated on the HandPD dataset, NeuroScript AI achieved 94.2% accuracy in classifying drawing samples into three neuromotor condition categories. These results suggest that image-based handwriting analysis, when paired with the right feature engineering, can reliably capture motor irregularities without requiring specialized equipment.

The broader implication is that systems like NeuroScript AI could reduce barriers to early neuromotor screening, particularly in settings where specialized clinical tools are unavailable.

VI. FUTURE WORK

Several directions could meaningfully extend this work. The current model is trained exclusively on spiral and meander drawings from the HandPD dataset. Expanding to other handwriting types—sentences, signatures, and free-hand sketches—would test how well the learned features generalize across drawing modalities.

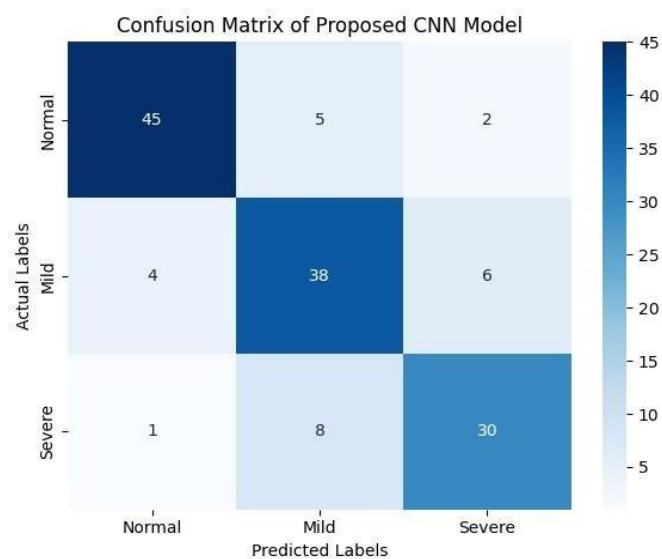


Fig. 3. Confusion matrix of the proposed CNN model showing classification performance for Normal, Mild, and Severe neuromotor conditions using the HandPD dataset.

The confusion matrix in Figure 3 shows that the model performs consistently across all three classes. Misclassifications are rare and tend to occur at class boundaries—for example, between Mild and Severe Irregularity—which is understandable given that these categories represent a continuum rather than discrete states. Normal cases were classified with particularly high accuracy, which is important for avoiding false positives in a screening scenario.

On the architecture side, Vision Transformers and hybrid CNN-Transformer models have shown strong performance on fine-grained image tasks and could improve the model's ability to capture long-range dependencies in drawing patterns. The NPI itself has room to grow: incorporating tremor frequency analysis, stroke curvature metrics, and micro-movement patterns could make it a richer descriptor of motor behavior.

Longer term, integrating NeuroScript AI with patient medical records and enabling longitudinal tracking could transform it from a screening tool into a continuous monitoring system—one that alerts clinicians to changes in motor function over time rather than providing a single snapshot.

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