IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 6, December 2026, pp. 5667~5677
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i6.pp5667-5677

Strikeout-aware graphonomics via deep atrous tan leaky convolutional neural networks and fuzzy bell tau inference

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Article Info

Article history:

Received Aug 17, 2025
Revised Aug 11, 2026
Accepted Aug 31, 2026

Keywords:

Deep learning
Graphonomics
Handwriting analysis
Personality classification
Strikeout detection

ABSTRACT

Handwriting reflects not only linguistic expression but also subtle psychological and behavioral traits. Conventional graphonomic systems often overlook critical dynamic features, such as strikeout patterns, writing pressure, and stroke continuity, that offer valuable insights into a person's emotional and cognitive state. To address these gaps, this paper proposes an enhanced graphonomic analysis framework based on a deep atrous tan leaky convolutional neural network (DATLCNN) integrated with a fuzzy bell tau inference system (FBTIS). The system incorporates a multi-stage pipeline involving contrast enhancement using contrast limited Lanczos interpolated adaptive histogram equalization (CLLIAHE), segmentation through Hough transform with tree-structured Parzen estimator (HTPT) tuning, stroke smoothing using adaptive local Gamma correction (ALGC), and dynamic feature extraction via quartic kernel density estimation (QKDE). These modules collectively support accurate character recognition and nuanced personality profiling. The proposed framework was evaluated using the IAM handwriting database and demonstrated superior performance across key metrics including character accuracy, segmentation rate, Dice coefficient, mean integrated squared error (MISE), and fuzzy inference timing. Comparative analysis shows that DATLCNN significantly reduces false recognition rates while FBTIS offers efficient, interpretable behavioral classification across 12 graphonomic traits under e-health, e-education, and e-society domains. The results confirm the system's effectiveness and suitability for applications in psychological assessment, education, and e-governance platforms.

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1. INTRODUCTION

Handwriting constitutes a particular type of personal expression that can tell great deals about the mental condition of a person, as well as his/her character traits [1]. This field is scientifically studied as graphonomics and is an integration of artificial intelligence and psychology to understand such patterns. As opposed to the stationary biometrics like facial recognition, the graphonomics is unique in its way because it

examines active and tHoughtful processes of writing [2]. As a result, the signals can be used as a powerful instrument of evaluating emotional conditions and psychological actions inside the body. One of the major benefits of handwriting analysis is that it is not an intrusive method. Handwriting is not easily disturbed like biometrics which is vulnerable to interference by environmental factors like light or movement, thus is simple to gather without interfering with the comfort level of its users. This dependability is essential to all e-governance systems such as e-health, e-education, and e-society where profiling e-citizens demand accuracy and privacy. Therefore, handwriting offers the scalability of the personalized services without intrusive monitoring.

Experts use traditional graphology to infer behavioral characteristics such as confidence and impulsiveness [3]. Nevertheless, this manual method is rather subjective and has no standardized requirements making it inconsistent in replication [4]. In order to overcome these shortcomings, modern attempts are directed at the analysis automatization based on machine learning (ML) and deep learning (DL) [5]. AltHough such approaches enhance objectivity, the existing automated systems continue to have operational flaws. Recent new advancements in DL have greatly increased this scope. In the example of [6], convolutional neural networks (CNNs) were applied to forecast the big five traits, and it was proven that automated feature extraction is more efficient. Likewise, Deore *et al.* [7] also matched the correlation of such static characteristics of baseline and slant with the emotional states in real time settings. Handling document structural integrity, Chaudhuri and Adak [8] recommended a graph-based approach to recover struck out text, and Nisa [9] used transformer models to handle cross outs in offline samples. It is noteworthy that the survey conducted by Deng *et al.* [10] has detected the existence of a critical gap in the analysis of the dynamics of cues, including hesitation marks, pressure, and so forth, which this framework is going to supplement.

The current models tend to focus on the analysis of the static features of the structure, such as slant and spacing without paying much attention to the detailed behavioral cues involved in the writing process [11]. The critical dynamic features that include pen pressure, hesitation marks and the specific pattern of strikeouts are often ignored even tHough they can provide important information about the state of emotions such as indecisiveness and friction. Moreover, the existing recognition mechanisms have problems related to technicalities, such as the errors in segmentation due to broken characters and noise signals of the environmental conditions such as the texture of papers. To address these limitations, this research introduces an enhanced graphonomics framework that integrates strikeout-aware analysis and dynamic feature extraction using a DL-based model known as deep atrous tan leaky convolutional neural network (DATLCNN). The proposed system incorporates multiple stages, including contrast enhancement, character segmentation, stroke smoothing, and fuzzy-based trait labeling. A novel fuzzy bell tau inference system (FBTIS) is employed to classify personality attributes across multiple domains relevant to e-citizenship. This multi-layered approach aims to produce a robust, explainable, and highly accurate system for both handwritten character recognition and psychological profiling.

Automated handwriting analysis for personality detection has evolved significantly with the integration of ML and DL techniques. Early approaches primarily relied on manually extracted graphological features like slant, spacing, pressure, and baseline to infer individual traits. However, recent works have leveraged CNN-based architectures to improve accuracy and objectivity of trait prediction. Lemos *et al.* [12] presented a CNN system that processes binarized handwriting images to simultaneously predict multiple personality traits such as optimism and pessimism, using enhanced pre-processing steps including contrast adjustment and Gaussian thresholding. Elngar *et al.* [13] established that DL models are more effective than the traditional ones in forecasting big five personality traits.

Pathak *et al.* [14] furthered this by using hybrid optical character recognition (OCR)-CNN-long short-term memory (LSTM)-fuzzy framework, which is used to extract both visual and cognitive features. At the same time, Patil and Mathur [15] created an artificial neural network (ANN)-based system of dual writer identification and inference of traits with the help of certain graphological markers on the IAM dataset. Discussing the issue of linguistic diversity, the authors [16], [17] have managed to use CNN structures to Kurdish and Devanagari scripts respectively. Moreover, Hasan *et al.* [18] concentrated on dynamic aspects through the use of digital tablets; their CNN-bidirectional gated recurrent unit (BiGRU)-bidirectional long short-term memory (BiLSTM) network could attain 99% accuracy, which confirmed the usefulness of text-independent analysis of biometrics.

To eliminate subjectivity, Ghods [19] used Mamdani fuzzy inference of Farsi samples, which had 82% accuracy, and Sati and Kumar [20] used a hybrid ANN-multilayer perceptron (MLP) model to predict certain structural characteristics. At the character level, Durga and Deepu [21] utilized a CNN ensemble and associated letters 't' and 'i' with personality markers. Moreover, Dhumal *et al.* [22] obtained behavioral profiling accuracy of approximately 98% through a self-attention deep dense network. Jiménez and Barrientos [23] confirmed the real-time graphonomic monitoring of the cognitive planning and quality of writing in children in the developmental domain.

In terms of document pre-processing, struck-out or noisy handwriting poses a significant challenge. Shivakumara *et al.* [24] addressed this by proposing a densely connected convolutional networks (DenseNet)-based classifier to detect and filter struck-out text before line segmentation, while Zhong *et al.* [25] implemented a dual-stage residual network (ResNet)-U-Net system to not only detect but also restore obscured words, improving the readability and analysis of handwritten responses. This is particularly useful in applications like automated answer script evaluation. Additionally, handwriting recognition systems tailored for language learning have been proposed. Gold *et al.* [26] developed a system to retain orthographic errors in handwritten German learner texts, demonstrating that preserving learner-specific spelling mistakes can enhance feedback mechanisms in educational platforms. These works underscore the growing convergence of graphology, computer vision, and DL for psychological assessment, biometrics, forensic analysis, and education. Despite progress, challenges, such as handling multilingual datasets, real-time processing, and interpretability of results remain active areas of research.

2. METHOD

The proposed system introduces a multi-stage, DL-enabled framework for personality and behavioral trait analysis through handwritten document recognition. The methodology encompasses image pre-processing, line-word-character segmentation, stroke refinement, dynamic behavior feature extraction, feature vector formulation, and classification using a novel DATLCNN integrated with a FBTIS. This pipeline effectively captures both physical and cognitive features embedded in handwriting, enabling a robust graphonomic profiling of e-citizens. Figure 1 gives the functional block diagram of proposed methodology.

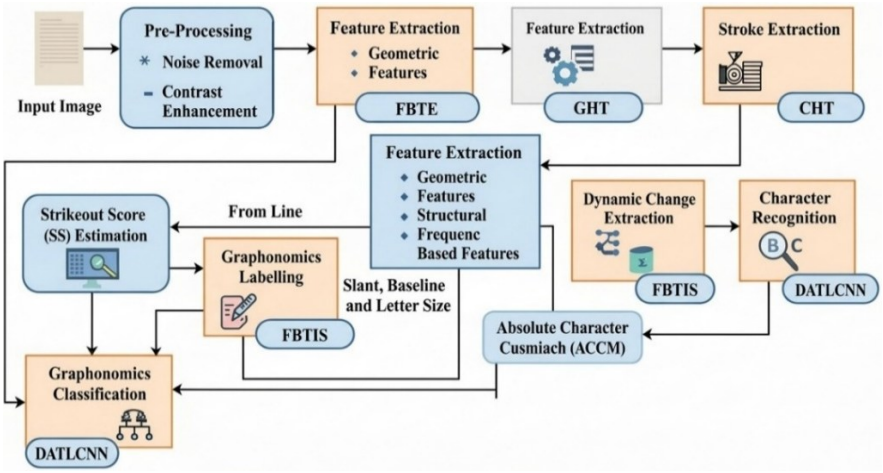


Figure 1. Function block diagram of proposed framework

2.1. Dataset and pre-processing

The system utilizes the IAM handwriting database [27], which contains real-world handwritten English text in various paragraph styles. Figure 2 shows the sample dataset copies. Raw input images often suffer from noise, uneven contrast, and illumination artifacts, requiring preprocessing for effective segmentation and feature extraction. Table 1 gives the summary of the dataset.

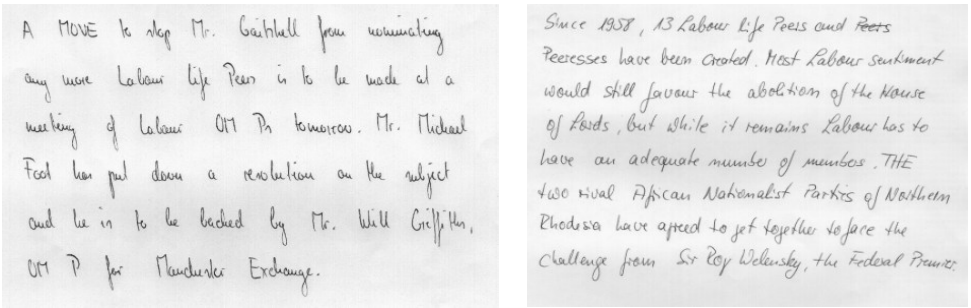


Figure 2. Samples from IAM dataset

Table 1. IAM handwriting dataset summary

Attribute	Details
Total writers	657
Total forms	1,539 handwritten forms
Total sentences	5,685
Total words	13,353
Total lines	13,353
Image format	Grayscale PNG
Annotation format	XML/ASCII
Scanning resolution	300 dpi
Language	English
Demographics	Mixed gender, age (18–60), left/right-handed

To address salt-and-pepper noise and speckles common in scanned documents, a median filter (MF) is applied. Unlike linear filters, the MF preserves edge information while eliminating outlier pixel intensities, ensuring the retention of crucial handwriting contours. Mathematically, the MF over a window W is defined as in (1).

$$I_{filtered}(x,y) = median\{I(s,t)|(s,t) \in W\} \quad (1)$$

To further improve visual clarity and feature detectability, a modified contrast limited adaptive histogram equalization (CLAHE) approach, termed contrast limited Lanczos interpolated adaptive histogram equalization (CLLIAHE), is used, result sample is given in Figure 3. Unlike traditional CLAHE, which may introduce blocky artifacts, the proposed method integrates Lanczos interpolation to achieve seamless tile blending and sharp contrast enhancement. Let T_i represent each tile and H_i its histogram. The contrast-limited histogram is represented in (2).

$$H_i' = \min(H_i, \theta) + \frac{\sum_j \max(0, H_j - \theta)}{N} \quad (2)$$

Where θ is the clip limit and N is the number of bins. Interpolation across tiles T_i and $T_i + 1$ is performed using Lanczos kernel $L(x)$ defined as (3).

$$L(x) = \begin{cases} \frac{\sin(\pi x)\sin\left(\frac{\pi x}{a}\right)}{(\pi x)^2}, |x| < a \\ 0 \quad , otherwise \end{cases} \quad (3)$$

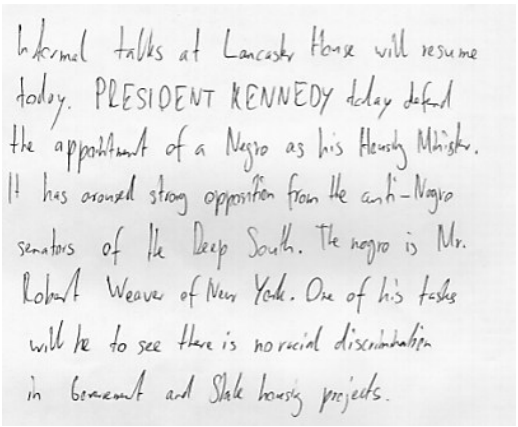


Figure 3. After contrast enhancement

After contrast enhancement, text components are separated hierarchically into lines, words, and characters using the Hough transform–tree-structured Parzen estimator (HTPT). This hybrid technique builds upon the classical Hough transform for line detection while employing a tree-structured Parzen estimator (TPE) to dynamically tune Hough parameters like angle resolution, minimum line length, and accumulator thresholds. Let θ and ρ represent the Hough parameters. HTPT models the tuning process via two conditional densities is given by (4), where x is a parameter set and $y^*$is a performance threshold. TPE selects x that maximizes the expected improvement, as given in (5).

$$l(x) = (p(x|y < y^*; g(x) = p(x|y \geq y^*) \quad (4)$$

$$EI(x) = \int_{-\infty}^{y^*} (y^* - y)\, p(y|x) dy \quad (5)$$

To eliminate discontinuities in broken characters, the active Laplacian of Gaussian contour (ALGC) method is employed. It fuses the internal energy minimization of active contours with gradient information extracted via Laplacian of Gaussian (LoG). The internal energy of the contour C(s) is defined in (6), where $\propto$ and β control tension and stiffness. The external energy from LoG is described mathematically in (7), with G_σ being a Gaussian kernel and $*$ denoting convolution.

$$E_{int} = \propto \left|\frac{dC}{ds}\right|^2 + \beta \left|\frac{d^2C}{ds^2}\right|^2 \quad (6)$$

$$E_{ext} = -|\nabla^2 G_\sigma * I| \quad (7)$$

Once the contour is refined, generalized Hough transform (GHT) is used to extract the medial skeleton of strokes. This algorithm ensures one-pixel width and connectivity of skeletons, facilitating feature extraction. The quartic kernel density estimation (QKDE) approach is used to model temporal handwriting dynamics like jerkiness and pressure variation expressed in (8), with the quartic kernel defined as in (9).

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{(x - x_i)}{h}\right) \quad (8)$$

$$K(u) = \frac{15}{16}(1 - u^2)^2 \quad for|u| \leq 1 \quad (9)$$

2.2. Classification model

The DATLCNN is an advanced DL architecture tailored for extracting both local and global features from handwriting images. The model is specifically engineered to handle the intricacies of graphonomic patterns by leveraging atrous convolution in combination with a novel activation function termed tan leaky rectified linear unit (ReLU). Atrous convolution plays a critical role in expanding the receptive field of the convolutional layer without increasing the number of parameters or the computational complexity. This allows the network to capture broader contextual information from the input image while preserving spatial resolution. Mathematically, the atrous convolution operation can be expressed as in (10).

$$y|i| = \sum_k x\,[i + r \cdot k] \cdot w[k] \quad (10)$$

In this context, x represents the input signal that is fed into the convolutional layer, while w denotes the filter or kernel weights used to perform the convolution operation. The parameter r is known as the dilation rate, which controls the spacing between the kernel elements during the convolution, effectively expanding the receptive field without increasing the number of parameters or computation. The index k refers to the position within the convolutional kernel, and $y|i|$ denotes the resulting output value at position i in the output feature map after applying the atrous convolution. This setup allows the model to capture more extensive contextual information from the input while preserving resolution and reducing computational cost. This formulation allows the network to learn hierarchical representations across varying spatial scales, making it particularly effective for analyzing handwriting variations such as size, stroke gap, and curvature.

The FBTIS interprets psychological characteristics by analyzing a set of handwriting features, including slant, baseline deviation, strikeout frequency, and absolute mismatch count. These features are extracted from the deep representations learned by the DATLCNN model and are evaluated using a set of fuzzy rules. Based on the degree of membership derived through the fuzzy inference mechanism, each handwriting sample is classified into one or more of twelve predefined graphonomic classes, which are grouped into three broad thematic domains: e-health, e-education, and e-society.

3. RESULTS AND DISCUSSION

3.1. Experimental setup

The research framework was tested on the basis of the IAM handwriting database, including a sample of 657 people. Python was used in an Intel Core i7 machine (16 GB RAM, Windows 10). Performance measurements were done on individual stages in the pipeline: i) character recognition: character error rate (CER), false negative rate (FNR), false positive rate (FPR), and accuracy; ii) segmentation

performance: processing time and rate; and CLLIAHE-based contrast enhancement: peak signal-to-noise ratio (PSNR).

To validate the stroke smoothing module, the Dice similarity coefficient was employed to measure the accuracy of reconstructed contours. The dynamic behavior features extracted through QKDE were quantitatively evaluated using the mean integrated squared error (MISE), which indicates the closeness of the estimated handwriting dynamics to the expected distribution. Finally, the proposed graphonomic classification performance was evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score across 12 graphonomic classes under e-health, e-education, and e-society domains.

3.2. Performance of character recognition model

The performance of the proposed character recognition model, DATLCNN, was benchmarked against several baseline DL models including deep convolutional neural network (DCNN), CNN, recurrent neural network (RNN), and deep neural network (DNN), as shown in Figure 4. Four key evaluation metrics were used for comparison: accuracy, precision, recall, and F-measure. Across all metrics, the proposed DATLCNN model consistently outperformed the competing models. Specifically, in terms of accuracy, DATLCNN achieved a peak performance close to 99%, significantly higher than traditional DCNN (approximately 96%), CNN (~94%), RNN (~92%), and DNN (~90%). This result validates the effectiveness of integrating atrous convolution with a tan leaky ReLU activation, allowing for better spatial resolution and feature stability.

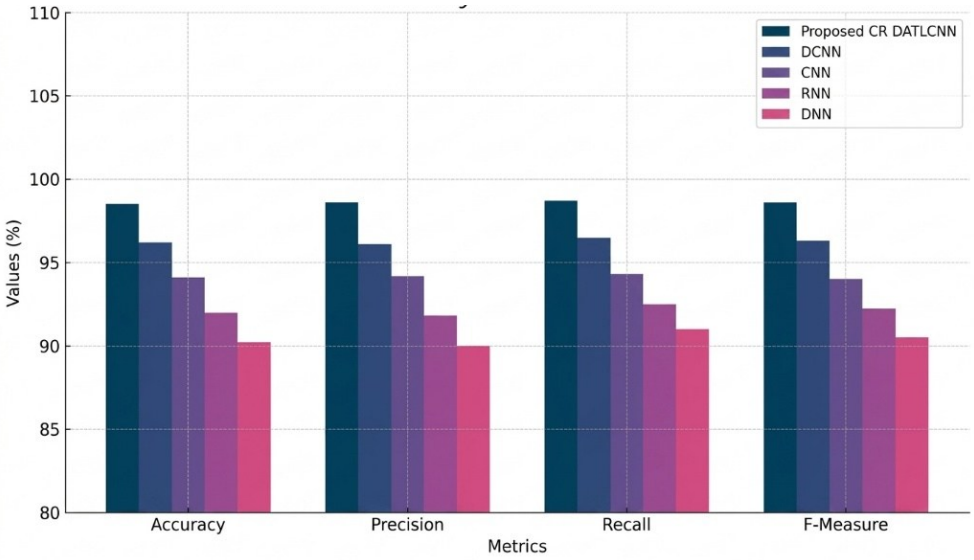


Figure 4. Character recognition performance metrics

DATLCNN was more precise making it successful in reducing false positives to maintain the semantic integrity. It achieved a recall of almost 99, which was much better than DCNN and CNN (94-96) and RNN/DNN models, being more sensitive to an instance of a character even tHough it was not perfectly stroked. The model, therefore, had an F-measure of close to 99, which is the best balance between precision and recall. All these findings substantiate DATLCNN as a powerful platform to have a character recognition with a high level of reliability and a graphonomic analysis at the same time.

The approximately 99% recognition accuracy obtained by DATLCNN is consistent with the performance reported by Hasan *et al.* [18], whose online pen-tablet-based model also achieved approximately 99% accuracy. However, their approach relies on dynamically captured temporal information, whereas the proposed method operates on offline scanned handwriting images, where stroke order and timing information are unavailable. DATLCNN also improves upon approximately 98% accuracy reported by Dhumal *et al.* [22]. This improvement can be attributed to atrous convolution, which captures multiscale handwriting patterns without substantially increasing model complexity, and the tan leaky ReLU activation, which supports stable feature learning. Nevertheless, because the studies use different datasets, acquisition modalities, and validation protocols, these results should be interpreted as evidence of competitive performance rather than a strict head-to-head comparison. Figure 5 shows the TPR and TNR comparison.

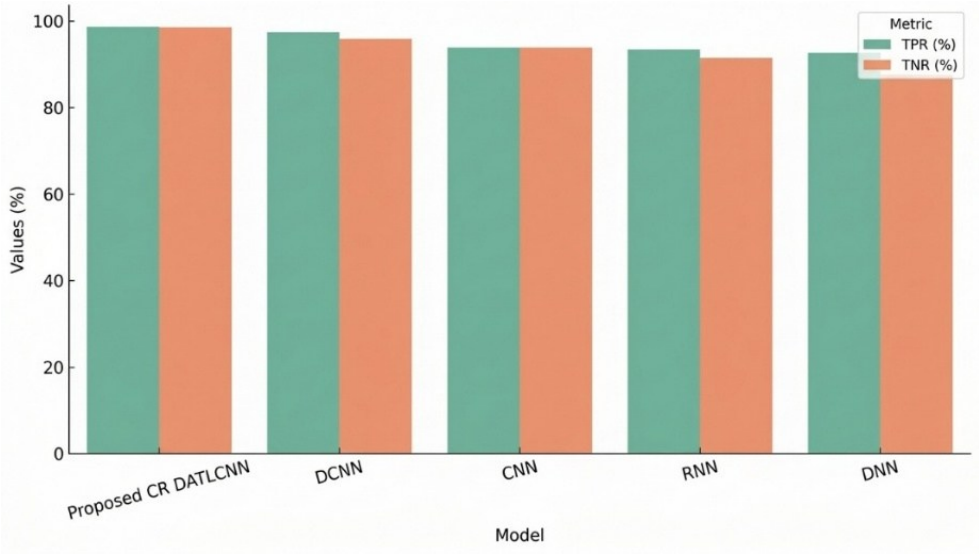


Figure 5. Comparison of TPR and TNR across models

3.3. Graphonomics labeling and rule processing time analysis

Figure 6 provides a comparative evaluation of the computational efficiency of different fuzzy-based systems with respect to three critical operations: fuzzification, defuzzification, and rule generation. These operations directly influence the real-time applicability of behavioral labeling systems, especially in graphonomics where interpretability and responsiveness are essential. The proposed FBTIS demonstrates the lowest processing time across all three operations, establishing its superiority in computational efficiency. Specifically, the fuzzification and defuzzification stages each complete in approximately 680 milliseconds, while rule generation is executed in just 420 milliseconds, significantly faster than all other compared techniques. This improvement is attributed to the optimized structure of the bell tau membership function, which offers sharp transition handling without incurring additional computational overhead.

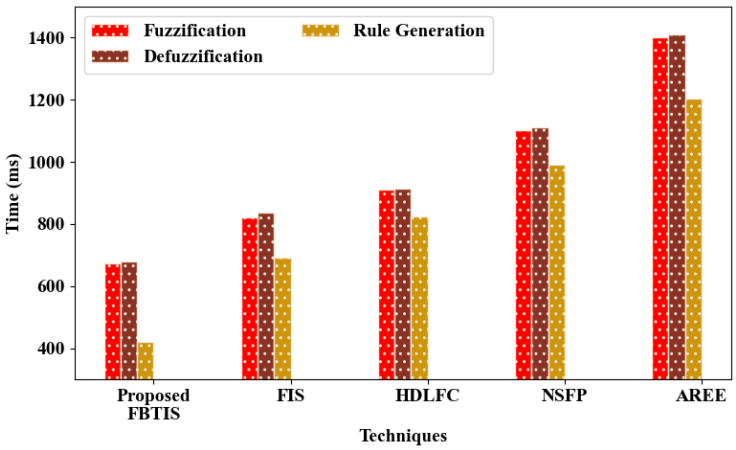


Figure 6. Graphonomics labeling and rule processing time analysis

Conversely, conventional fuzzy inference system is more latent, the fuzzification/defuzzification was more than 800 ms and the rule generation took 700 ms. Hierarchical approaches such as horizontal and vertical line, diagonal line, and fully closed (HDLFC), neuro-semantic fuzzy process (NSFP) increase these prices to 900-1,100 ms, whereas adaptive rule extraction engine (AREE) is the least efficient with 1,400 ms and 1,200 ms respectively. Such delays do not support real-time deployment. On the other hand, the suggested FBTIS system is more computationally efficient and more rule interpretable. Its reduced

processing time renders it suitable in the real-time analysis of graphs and personality inference of e-governance systems.

3.4. Stroke continuity smoothing and contour quality analysis

Figure 7 gives an assessment of stroke smoothing techniques using Silhouette and Dice scores on the separation of the boundaries and the contour preservation of a boundary–which are important in terms of geometric accuracy. THough the proposed ALGC generates the lowest raw values (Silhouette = 4,100, Dice = 4,200), this value provides a representation of controlled smoothing with a minimum amount of distortion. The ALGC therefore, is a good compromise between contour fidelity and noise reduction, which guarantees the structural integrity of strong downstream character recognition. The classic active contour techniques (5,200-5,600) provide a medium level of enhancement, but lose boundary in the low-resolution areas. On the contrary, the Bezier and basis spline (B-Spline) methods have better scores but they may simplify natural curvature leading to recognition errors. In spite of the highest metrics of the moving average method (Dice is the highest at 11,000, silhouette is the highest at 9,800), it loses fine strokes. This de-noising allows the removal of subtle writer peculiarities that are important in doing personality inferences, sacrificing diagnostic richness to geometrical regularity.

3.5. Graphonomic classification error rate analysis

Figure 8 presents a comparative evaluation of the FPR and FNR for different DL models applied to graphonomic classification tasks. These two metrics are critical in assessing the reliability and robustness of a classification system, especially when used for psychological trait prediction from handwriting. The proposed graphonomic classification based on deep atrous tan-leaky convolutional neural network (GC-DATLCNN) model exhibits the lowest error rates across both metrics, with an FPR of approximately 2.2% and an FNR of around 1.9%. This indicates that the model is highly precise in classifying the correct behavioral traits and rarely misclassifies either positive or negative cases. The superior performance can be attributed to the model's integration of atrous convolutions, which enhance contextual understanding, and the use of the tan leaky ReLU activation function, which ensures stability during training and inference. This analysis strongly supports the effectiveness of the DATLCNN framework for graphonomic classification, emphasizing its ability to significantly reduce misclassification errors. This reliability is essential in practical deployments where accurate psychological inference from handwriting can inform decision-making in fields such as education, mental health, and e-governance.

Graphonomic classification results have been corroborated by previous literature on personality prediction research as well. In one of the studies, Ghods [19] used the Mamdani fuzzy inference system to classify the personality with 82% accuracy. On the other hand, the proposed method yielded 2.2% and 1.9% false positives and negatives respectively. The advantage in the system is the result of the fusion of DL feature extraction with bell tau fuzzy membership function that helps handle overlapping behavioral categories in a better manner. Additionally, according to the researchers [24], [25], it is essential to detect and correct strikeouts from handwritten documents during analysis. However, in contrast to these researchers who focused on strikeouts as noise in recognition, the proposed system considers strikes out as graphonomic cues for behavioral classification as well.

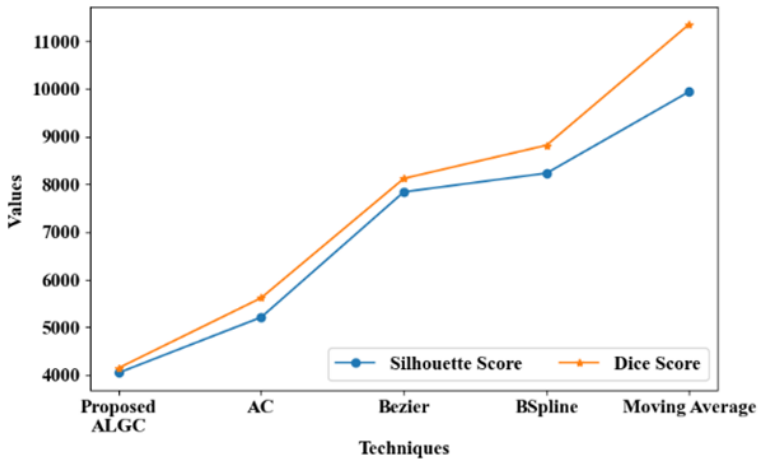


Figure 7. Stroke continuity smoothing and contour quality analysis

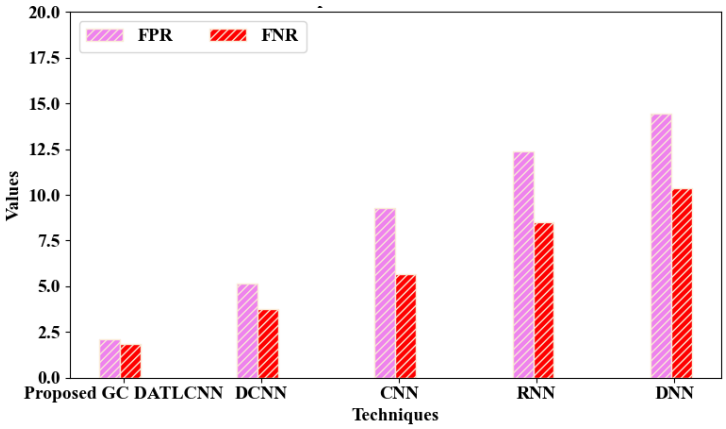


Figure 8. Graphonomic classification error rate analysis

3.6. Visual output analysis

The graphical user interface (GUI) output in Figure 9 illustrates the final stage of the proposed graphonomic analysis system, wherein handwritten input is processed and mapped to a specific behavioral class based on extracted features. The interface is intuitive and functionally segmented, showcasing a comprehensive flow from segmentation to behavioral interpretation. The inference is likely driven by features such as consistent letter spacing, assertive stroke thickness, minimal tremors, and well-defined baselines, all of which correlate with decisiveness and self-assurance. The strikeout of "begin" may further indicate a deliberate effort to refine expression, enhancing the profile's alignment with traits of pride and self-confidence. The output reflects the success of the integrated DATLCNN-FBTIS architecture, which leverages dynamic handwriting cues and structural features to deliver an interpretable, real-time behavioral summary. The clean interface also supports user interaction and transparency, making it suitable for educational, psychological, or e-governance applications.

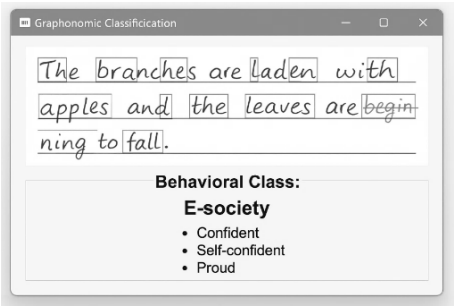


Figure 9. Graphonomic classification GUI

4. CONCLUSION

This paper presents a comprehensive and robust framework for graphonomic analysis that leverages both structural and behavioral characteristics of handwriting to classify psychological traits among e-citizens. By incorporating dynamic stroke analysis and underutilized cues such as strikeouts, the proposed DATLCNN-FBTIS architecture significantly advances the capabilities of automated handwriting interpretation. The integration of contrast enhancement, adaptive segmentation, contour smoothing, and fuzzy-based inference provides a holistic pipeline that is not only accurate but also interpretable and responsive in real time. Experimental results demonstrate that the proposed approach consistently outperforms traditional methods across various evaluation metrics, including recognition accuracy, segmentation quality, classification precision, and computational efficiency. The low error rates in false positive and false negative classifications, along with superior smoothing and dynamic modeling, validate the system's applicability in real-world scenarios. Furthermore, the GUI-based visualization offers an intuitive and transparent interface for end-users, enhancing accessibility for psychological, educational, and governance-related applications. This work contributes a novel and practical direction in the field of graphonomics, laying the groundwork for future research that could expand into multilingual, cross-cultural handwriting datasets and real-time handwriting capture systems for broader behavioral profiling.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Ujwal Urubail Jayaprakash				✓	✓		✓			✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in International Journal on Document Analysis and Recognition at https://doi.org/10.1007/s100320200071, reference [27].

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