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Original Article

Particle Swarm Optimization-Convolutional Neural Network (PSO-CNN): An Optimized Deep Learning Model for Personality Recognition From Social Media Profiles

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Abstract

Recognition of users' accounts on social media platforms remains challenging, particularly when profile images are hidden or users maintain multiple accounts. This paper proposes and validates a novel Particle Swarm Optimization-Convolutional Neural Network (PSO-CNN) hybrid model that fundamentally addresses the critical challenge of hyperparameter optimization in automated personality recognition from social media. Unlike existing approaches that rely on manual trial-and-error configuration, the PSO-CNN framework uniquely automates the discovery of optimal architectural parameters by integrating the global search capabilities of PSO with the feature extraction power of CNNs. This automation eliminates subjective design choices, uncovers non-intuitive parameter combinations that human experts might overlook, and ensures consistent performance across diverse personality types without manual adjustment. It automatically selects optimal learning rates, filter configurations, and regularization settings for classifying users according to the Myers-Briggs Type Indicator framework. Evaluated on a Twitter dataset of 8,328 users, the PSO-CNN-optimized model achieved significant performance with 84.5% test accuracy and 98.2% F1-score, representing improvements of 14.6% and 21.8%, respectively, over a standard CNN baseline. The optimized model demonstrated robust performance across all 16 personality types, maintaining high precision (98.9%) and recall (99.8%) with a low false positive rate of 0.3% while converging to optimal parameters within 65 PSO iterations. These findings empirically validate that metaheuristic optimization substantially enhances deep learning performance for psychometric applications, offering an efficient, scalable solution for personality recognition with practical implications for personalized systems, human-computer interaction, and computational social science. The study establishes PSO-CNN as an effective paradigm for advancing automated personality assessment while providing a foundation for future research into multimodal integration and cross-platform generalization.

Categories: Ensemble Learning, AI applications, Data Mining

Keywords: human emotion recognition, particle swarm optimization, convolutional neural network, social media analytics, computational psychology, deep learning optimization

Introduction

The consistent patterns of actions, cognition, and behavior that characterize individuals over time and across situations represent an individual's personality [1]. Humans exhibit different characters and respond to similar situations or events separately based on their personality. In psychological science, a set of Five-Factor Model, commonly termed the "Big Five," continues to serve as the predominant framework for organizing personality traits. These Big Five also provides dimensions for classifying traits into dimensions to include Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Concurrently, the Myers-Briggs Type Indicator (MBTI) remains extensively utilized in organizational contexts despite ongoing debates regarding its psychometric properties [2]. The computational inference of personality traits from digital footprints, known as personality recognition, has gained significant momentum with the proliferation of Online Social Networks through platforms such as Twitter, Facebook, Instagram, Tiktok and Weibo. These platforms host vast quantities of user-generated content that implicitly reflect psychological characteristics through linguistic patterns, social connections, and behavioral preferences [3]. Research demonstrates that digital traces from social media can predict personality traits with accuracy comparable to or exceeding traditional self-report measures [4].

In today's world, personality recognition systems are becoming indispensable in many fields and organizations, as they provide substantial value across multiple domains, including personalized recommendation and authentication systems [5], mental health monitoring [6] with artificial intelligence models [7], and human resource management and security informatics [8,9]. Traditional personality assessment methodologies, primarily reliant on questionnaires and interviews, face inherent limitations in scalability, cost efficiency, and susceptibility to self-presentation biases [10]. With the emergence of deep learning architectures, personality recognition tasks have proven to be effective, capable of learning hierarchical feature representations [11] from complex, high-dimensional social media data without extensive manual feature engineering [12]. Among these, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in extracting local semantic patterns from textual data that correspond to personality traits [13]. However, optimizing CNN architectures [14] for personality recognition presents significant challenges, including the selection of appropriate hyperparameters, filter configurations, and weight initializations that substantially impact model performance.

Metaheuristic optimization algorithms offer promising solutions to these challenges. Particle Swarm Optimization (PSO), a population-based stochastic optimization technique inspired by social behavior, has been successfully applied to optimize neural network parameters, demonstrating superior efficiency in navigating complex search spaces [15]. Recent studies indicate that PSO-enhanced neural networks achieve improved convergence rates and predictive accuracy across various classification tasks [16]. In this paper, an optimized PSO-CNN model for personality recognition from Twitter data is developed to address the optimization challenges inherent in deep learning approaches to personality recognition. It utilizes PSO to automatically configure CNN parameters, thereby enhancing feature extraction capabilities and classification performance. By synthesizing advances in deep learning with swarm intelligence optimization, this paper aims to advance the state-of-the-art in scalable, accurate computational personality assessment.

Review of related works

Our review of related works commenced with the methodological evolution in computational personality recognition from social media, tracing the progression from feature-engineered machine learning to optimized deep learning frameworks. These studies are examined to contextualize the research gaps that motivate the proposed PSO-CNN hybrid model.

Initial personality recognition research predominantly relied on traditional machine learning algorithms paired with extensive feature engineering. Xue et al. [17] employed label distribution learning with 113 handcrafted features from Sina Weibo microblogs, while some researchers [18] used LASSO regression on Facebook Likes data from 92,255 users to predict Big Five traits. Although these studies established baseline methodologies and demonstrated the feasibility of automated trait inference, with LASSO achieving notable accuracy for Extraversion and Openness, they were fundamentally limited by their dependence on manually curated features. Critical performance metrics like computational efficiency and sensitivity were ignored by some developed models. Furthermore, previously developed personality recognition models struggled to scale effectively with the high-dimensional, unstructured nature of social media data.

The development of shallow models poses a great limitation, which catalyzed a significant shift towards deep learning architectures, which excel at automatically learning hierarchical feature representations from raw data. Pioneering work of researchers [19] demonstrated the superiority of CNNs over both recurrent networks and fully connected networks for personality detection from Facebook status updates, achieving 60.0% accuracy. This finding was corroborated by Tandera et al. [20], whose deep learning frameworks reached 74.17% accuracy, and by researchers [17] who used hierarchical attention-based CNNs to extract deep semantic features that enhanced regression model performance. Parallel to architectural advances, research focused on optimizing feature extraction from rich metadata. Tareaf et al. [21] innovatively mapped Facebook Likes to page categories, using this metadata to predict psycho-demographic profiles with up to 87% accuracy in large-scale studies. However, a consistent critique across these deep learning studies was the inadequate consideration of model optimization, particularly the computational cost of training and the heuristic, often suboptimal, process of tuning hyperparameters and network architectures.

To address performance ceilings, recent studies have increasingly turned to ensemble methods and multimodal fusion. The work described in [22] combined optimization techniques such as hyperparameter tuning with ensemble learners (XGBoost, Super Learner) to achieve perfect area under the receiver operating characteristic curve scores for Indonesian Facebook data. Similarly, XGBoost outperformed other selected machine learning models with an accuracy of 74.2% when tested on personality traits and feature sets [23]. A deep neuro-fuzzy model developed by Johnson et al. [24] utilized a collection of user data to predict work performance ratings linked to individual personalities. The frontier of personality recognition has expanded beyond text to include multimodal data. Rodriguez et al. [25] pioneered weakly supervised learning from images tagged with personality-relevant hashtags, showing that visual content could reliably infer traits. Another study advanced this further by fusing image and text features via ontology-based graphs and neural networks, achieving high classification results [26]. Other sophisticated approaches include findings reported in [27-29], which involve the fusion of multiple pre-trained language models (BERT, RoBERTa) and a hybrid CNN model that leveraged combined feature extraction to boost personality classification performance [30], respectively.

Despite these advancements, a critical review of the literature reveals a persistent and significant gap: the lack of a systematic, efficient, and automated optimization strategy for deep learning models in the personality recognition domain. While studies have successfully applied complex architectures and fusion techniques [31], they frequently treat network design and hyperparameter selection as a manual or grid-search process, which is computationally expensive and not guaranteed to find optimal configurations [12]. This gap presents a major bottleneck for developing scalable, high-performance personality recognition systems. Consequently, this research identifies a compelling opportunity to integrate metaheuristic optimization algorithms, specifically PSO, with deep learning. Inspired by successful applications of PSO for neural network optimization in other fields [16], this work proposes a novel PSO-CNN hybrid framework. This approach aims to automate the search for an optimal CNN architecture and parameter set tailored for personality recognition from Twitter data, thereby directly addressing the optimization challenge underexplored in prior work while leveraging the proven feature-learning power of deep convolutional networks.

Materials And Methods

The methodology adopted facilitates personality trait identification through systematic analysis of social media content, optimizing model accuracy and computational efficiency. The developed model incorporates a structured five-phase pipeline: data collection, preprocessing, PSO-CNN optimization, knowledge base development, and personality trait recognition.

Data collection and description

We utilized a secondary multidimensional dataset from a publicly available database repository known as Kaggle. The collated Twitter dataset was hosted by Sanket Rai on his personal page with the description "Twitter MBTI Personality Types Dataset" through the Twitter API between December 2019 and March 2020 (UTC timestamps available in the repository metadata). It comprises 8,328 users information who self-reported their MBTI personality types in their profile descriptions. Each user profile contains five distinct features for user identification, as shown in Table *1*. The MBTI further aids in categorizing individuals into 16 personality types, as shown in Table *2*, with their description based on four dichotomies including Extraversion (E) vs. Introversion (I), Sensing (S) vs. Intuition (N), Thinking (T) vs. Feeling (F), and

Judging (J) vs. Perceiving (P). The graph in Figure 1 shows the sample of each category of users collected for this research. Following collection, all user identifiers were removed, and tweet text was anonymized to prevent re-identification. The dataset contains no demographic information that could enable discriminatory analysis.

S/N	Features Classification	Description
1.	Identity	User ID, screen name, location, profile description, verification status
2.	Behavioral	Followers count, friends count, statuses count, retweet/favorite statistics, media/hashtag/URL/mention frequencies
3.	Linguistic Features	More than 200 recent tweets per user collected between December 2019 and March 2020
4.	Network Features	Directed unweighted graph representation of follower-followee relationships
5.	Psycholinguistic Features	MBTI personality type labels for 16 categories (Table 2)

TABLE 1: User profile features and description

MBTI, Myers-Briggs Type Indicator

S/N	Personality Type	Personality Traits
1	INFJ - The Counsellor	Empathetic, perceptive, idealistic
2	INFP - The Healer	Idealistic, imaginative, compassionate
3	ENFP - The Champion	Enthusiastic, imaginative, charismatic
4	INTJ - The Mastermind	Strategic, logical, independent thinkers
5	INTP - The Architect	Analytical, curious, inventive thinkers
6	ENFJ - The Teacher	Charismatic, empathetic, inspiring
7	ENTJ - The Commander	Assertive, strategic, goal oriented
8	ENTP - The Visionary	Innovative, curious, resourceful
9	ISFJ - The Protector	Warm, nurturing, considerate
10	ISTJ - The Inspector	Realistic, organized, detail-oriented
11	ESTJ - The Supervisor	Organizational, practical, decisive
12	ESFJ - The Provider	Warm, social, nurturing
13	ISTP - The Craftsman	Pragmatic, adaptable, hands-on
14	ISFP - The Composer	Artistic, sensitive, gentle
15	ESTP - The Dynamo	Energy, action-oriented, spontaneous
16	ESFP - The Performer	Outgoing, social individuals

TABLE 2: MBTI personality types and traits

I/E = Introversion/Extraversion
N/S = Intuition/Sensing
F/T = Feeling/Thinking
J/P = Judging/Perceiving
MBTI, Myers-Briggs Type Indicator

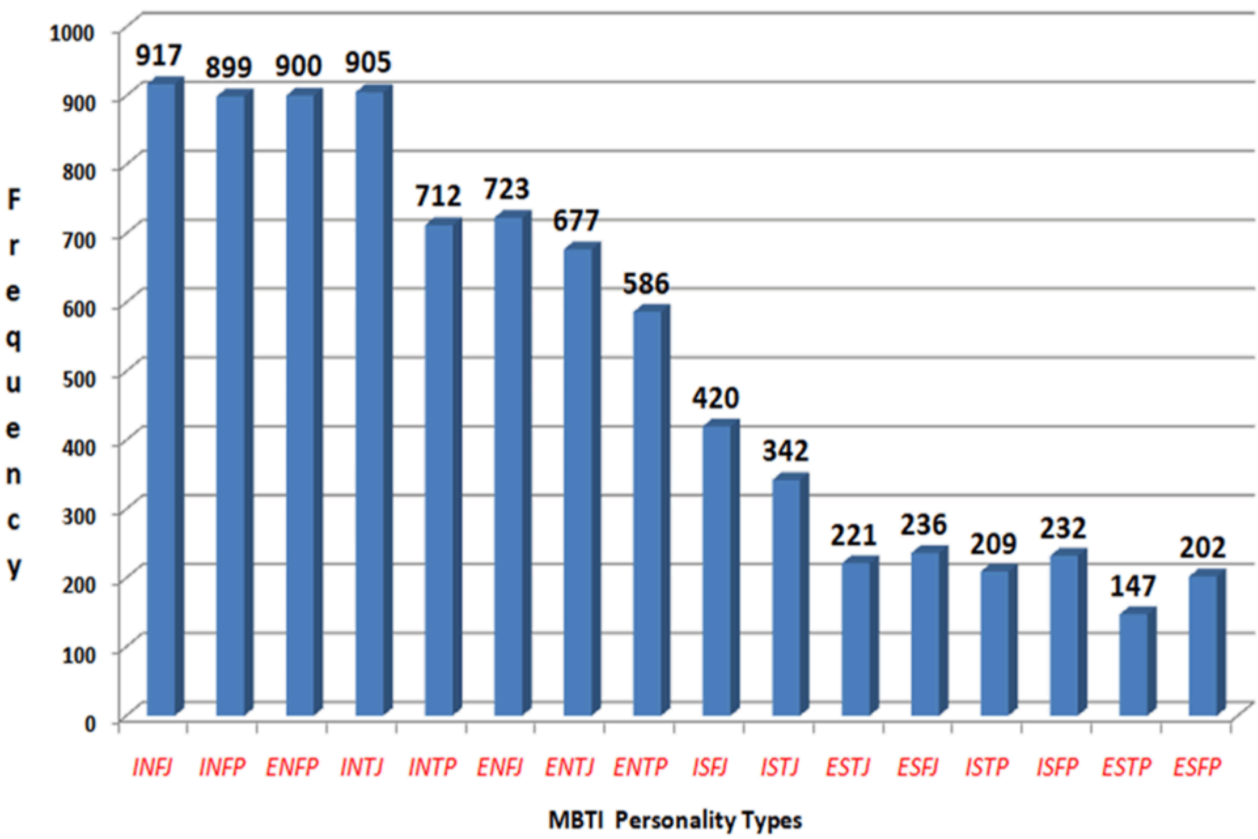

FIGURE 1: Personality description of collected samples

I/E = Introversion/Extraversion
N/S = Intuition/Sensing
F/T = Feeling/Thinking
J/P = Judging/Perceiving
MBTI, Myers-Briggs Type Indicator

Data preprocessing pipeline

During this phase, textual features were extracted from tweet content following standard preprocessing procedures listed in the preprocessing phase. Network features were also obtained from publicly available follower/friends relationships and retweet patterns, capturing social connectivity without requiring direct network topology analysis. This preprocessing phase enhances data quality through noise reduction and features (follower count, friend count, follower/following ratio, retweet frequency and frequency of mentions) standardization following these stages.

i. Data Integration: The raw MBTI Twitter data was consolidated from multiple unstructured sources into a single structured dataset, unifying user profiles, tweets, network connections, and behavioral metrics into a cohesive analysis-ready format.

ii. Text Normalization: Tweets underwent standardization through removal of non-English content, URLs, symbols and emotions, followed by contraction expansion, lowercasing, and selective stop-word removal that preserved negation terms crucial for sentiment analysis.

iii. Short Word Filtering: Words with two or fewer characters were systematically eliminated from the corpus, removing common but uninformative terms while preserving meaningful abbreviations and domain-specific short forms.

iv. Alphanumeric Cleaning: Mixed alphanumeric tokens were removed to eliminate noise and deceptive content patterns, though numeric counts were preserved as potential features indicating spam characteristics.

v. Stemming: The Porter Stemming Algorithm reduced words to their root forms, collapsing morphological variants to reduce feature dimensionality while maintaining semantic consistency across the dataset.

vi. Tokenization: Word piece tokenization segmented text into meaningful sub-word units, enabling n-gram representation that captured both short-term patterns and longer contextual relationships in tweet content.

vii. Feature Vectorization: A binary weighting scheme transformed tokenized text into numerical vectors, representing document-term relationships through a simple yet effective presence/absence encoding suitable for subsequent deep learning processing.

Dataset distribution and partition strategy

All collated tweets in the MBTI Personality Twitter Dataset fall in a consistent range between December 2019 and March 2020. In order to ensure contemporaneous social media activity representation for our robust model evaluation, the dataset was partitioned using 10-fold cross-validation with a 70/15/15 split for training, validation, and testing, respectively, translating to approximately 5,830 users for training and 1,249 users each for validation and testing. Stratified sampling was employed throughout this partitioning to preserve the original class distribution across all data splits, thereby preventing sampling bias and ensuring that each subset accurately reflected the overall population characteristics.

The PSO-CNN personality recognition framework

The personality recognition framework shown in Figure *2* utilized a VGG-19-based CNN architecture specifically adapted for text-based classification tasks following a systematic work flow depicted in Figure *3*.

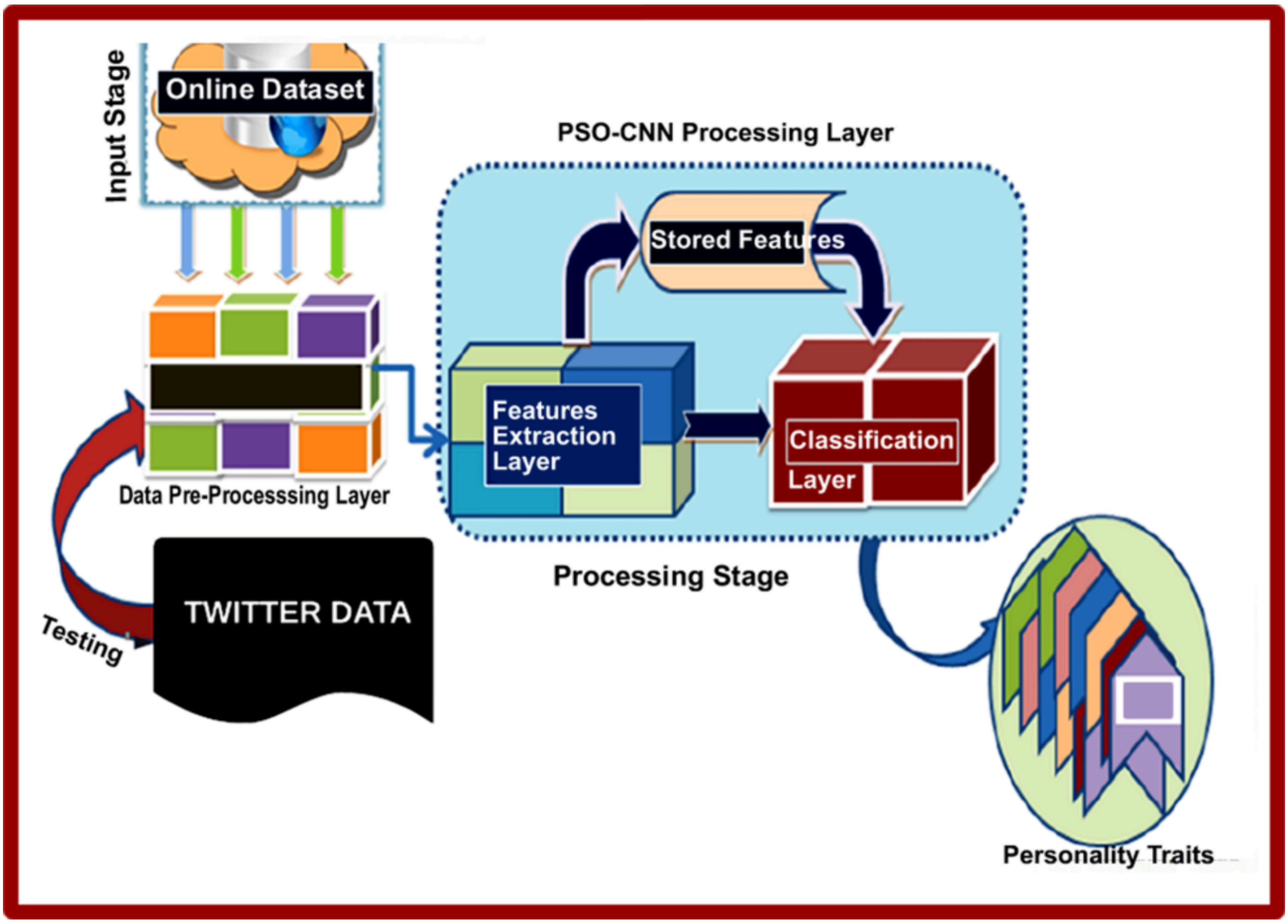

FIGURE 2: The personality recognition framework

PSO-CNN, Particle Swarm Optimization-Convolutional Neural Network

The base CNN employs multiple convolutional blocks for hierarchical feature extraction from user-generated text, capturing increasingly complex linguistic patterns through successive layers. Following each convolutional operation, max-pooling layers perform dimensionality reduction while preserving the most salient semantic features. The extracted features then pass through fully connected layers incorporating dropout regularization, batch normalization, flattening, and dense transformations to integrate multidimensional representations. The architecture culminates in an output layer with SoftMax activation, enabling precise 16-class classification corresponding to the complete MBTI personality type taxonomy. This robust CNN framework provides the foundational learning capacity that PSO subsequently enhances through systematic hyperparameter tuning.

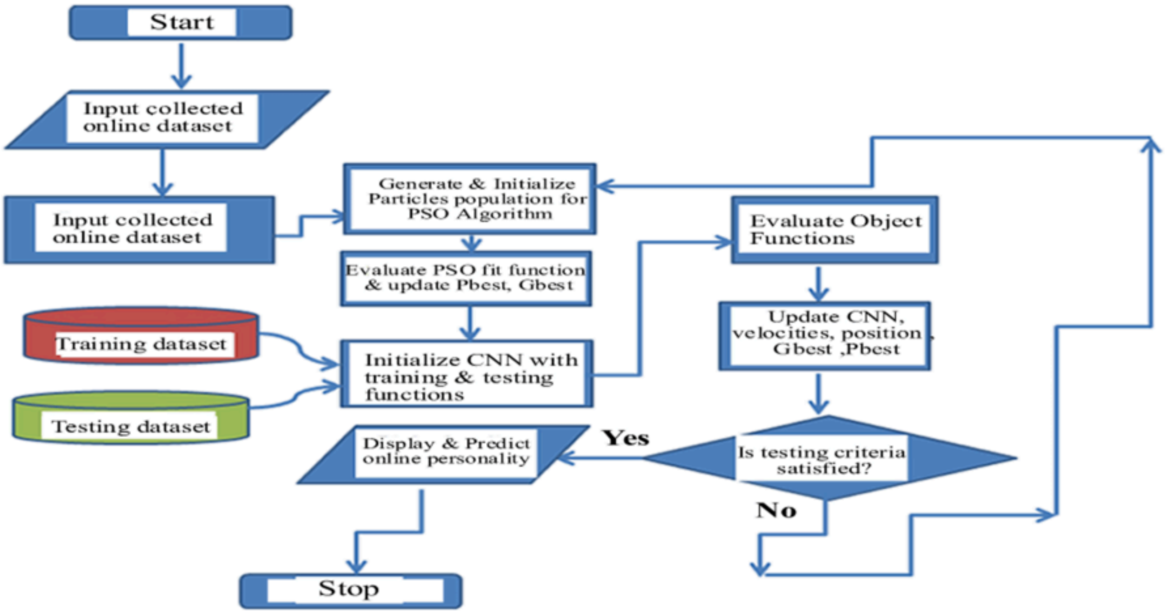

FIGURE 3: The PSO-CNN model personality recognition model development workflow

PSO-CNN, Particle Swarm Optimization-Convolutional Neural Network

The PSO-CNN model personality recognition optimization framework

PSO optimizes CNN hyperparameters to enhance recognition performance through particle encoding scheme. Each particle represents a set of hyperparameter including learning rate, filter counts, dense layer units, dropout rates, and batch size. The optimization objective function minimizes classification error with the given formula in Equations 1-5, respectively.

$$\text{Minimize:} \min_{(G_{\text{best}},\, F_e)} \phi\big(y(\text{fit})\big) \tag{1}$$

Subject to:

$$C1 : 0 \leq h(x(t),\, w(t),\, Gbest,\, fit) \leq 1, \qquad fit \in F_e \tag{2}$$

$$C2 : 0 < w(t) < 1 \tag{3}$$

$$C_3 : \; w(t) = Iw(t) \quad \text{if } Iw(t) \geq w(t) \tag{4}$$

otherwise

$$C3 : w(t) = w(t)\text{if } Iw < w(t) \tag{5}$$

where $x(t) \in \mathbb{R}^n$ represents the feature pattern vectors of the CNN state weight variables. The entire state vector is denoted as $y = [x]$, where x is the set of weight parameter settings of CNN. On the horizon $F_e = [fit]$ of the weight parameter, the problem is defined. The weight parameter-dependent control variables of PSO, $G_{\text{best}} \in \mathbb{R}^n$, and decision factors for the optimization could include the final weight parameter. The purpose of optimization is to discover the best set of choice variables to reduce the objective function $\varnothing$, that is, $\phi\big(y(fit)\big)$, to the smallest possible value. Constraints

C1, C2, and C3 limit the search space for finding the best solution, which describe, appropriate weight parameter requirements to be fulfilled during feature extraction and classification level. The study considered weight constraint $w(t)$ and feature constraint (h).

Furthermore, the PSO-CNN operates through a systematic integration of feature engineering, swarm intelligence optimization, and deep learning classification. During feature extraction, textual data undergoes WordPiece tokenization and is transformed into n-gram representations using a vector space model with binary weighting represented by the equation $d_j = (w_{1j}, w_{2j}, w_{3j}, \ldots, w_{mj})$ where d_j denotes the jth content of personality Facebook data to be recognized and wij denotes the binary weighting of the ith term in the jth, which is the weight of the term.

This representation preserves stylistic features such as normalized word length counts while reducing dimensionality. The PSO component then searches the hyperparameter space to minimize the classification error function, automatically identifying optimal CNN configurations for filter sizes, layer depth, and learning rates. These optimized parameters configure a CNN architecture enhanced with self-attention mechanisms, where feature vectors pass through multiple fully connected layers with ReLU activation and batch normalization. The attention module applies softmax weighting to emphasize salient linguistic patterns, with PSO-optimized attention weights selectively amplifying relevant features while suppressing noise. Finally, the tuned CNN processes the weighted feature representations through convolutional and pooling layers for hierarchical pattern extraction, culminating in SoftMax-based classification of the 16 MBTI personality types. This synergistic framework reduces computational complexity through automated hyperparameter selection while improving generalization by adaptively focusing on discriminative textual features.

Model evaluation

Model performance was evaluated using a comprehensive suite of metrics derived from the model's confusion matrix analysis to ensure thorough assessment across multiple dimensions. True Negative (TN), False Negative (FN), False Positive (FP), and True Positive (TP) were all included. These terms were used to compute the precision, recall, false positive rate, F-measure, and overall accuracy scores and represented as shown in Equations 6-10.

$$\text{Precision} = TP/(TP + FP) * 100 \tag{6}$$

$$\text{Recall} = TP/(TP + FN) * 100 \tag{7}$$

$$\text{False Positive Rate (FPR)} = FP/(TN + FP) * 100 \tag{8}$$

$$\text{F-Measure} = 2 * ((Precision * Recall)/(TN + FP)) \tag{9}$$

$$\text{Accuracy} = ((TP + TN)/(TP + TN + FP + FN)) \tag{10}$$

Accuracy served as the primary measure of overall classification correctness across all personality types. Precision quantified the positive predictive value for each specific personality type, indicating the proportion of correctly identified positives among all instances predicted as that type. Recall (or sensitivity) measured the true positive rate for each class, representing the model's ability to correctly identify all relevant instances of a given personality type. The F1-Score provided a balanced assessment by calculating the harmonic mean of precision and recall, offering a single metric that accounts for both false positives and false negatives.

Additionally, the false positive rate (FPR) was computed to determine the proportion of negative instances that were incorrectly classified as positive. To ensure statistical robustness, all metrics were calculated using 10-fold cross-validation, which provided both mean performance scores and standard deviations. Statistical significance was assessed through paired t-tests with $\alpha = 0.05$ to compare the PSO-CNN model against each baseline approach. Furthermore, computational efficiency was analyzed by recording key metrics including training time, inference time, and memory usage throughout the experimental process.

Results And Discussion

The results obtained from the implementation of PSO-CNN technique are clearly depicted in Figures 4-9. Firstly, three models (baseline, Long Short-Term Memory [LSTM] network, and CNN) with their default parameters listed in Table 3 were used to perform predictions. The results from these baseline comparisons measured by metrics including sensitivity, FPR, precision, accuracy, F1-Score, and Area-Under-Curve (AUC) are depicted in Figures 4-9, respectively. To validate the PSO-CNN optimization, series of tests were conducted to determine how the model performed at predicting personality traits after it has been configured with optimization parameters contained in Table 4 and Table 5, respectively.

Models	Baseline Model (Traditional Machine Learning)	Long Short-Term Memory (LSTM) Network	Standard Convolutional Neural Network
Hyperparameters	Algorithm: Support Vector Machine with radial basis function kernel. Features: Handcrafted psycholinguistic features (Linguistic Inquiry and Word Count categories) + behavioral metric. Implementation: Scikit-learn's Support Vector Classifier with default parameters	Architecture: Two-layer bidirectional LSTM with 128 units per layer. Embedding: Pretrained GloVe embeddings (300 dimensions). Regularization: Dropout rate of 0.3 between layers. Output: Softmax layer for 16-class classification	Architecture: Three parallel convolutional layers with filter sizes (3, 4, 5). Filters: 128 filters per convolutional layer. Pooling: Global max-pooling, followed by two dense layers (512, 256 units). Optimization: Adam optimizer with learning rate 0.001

TABLE 3: Default models's hyperparameters

Parameter	Value	Description
Swarm Size	30	Number of particles in the swarm
Iterations	100	Maximum optimization iterations
Cognitive Coefficient (c_1)	1.49445	Influence of particle's best position
Social Coefficient (c_2)	1.49445	Influence of swarm's best position
Inertia Weight (ω)	$0.9 \rightarrow 0.4$	Linearly decreasing over iterations
Search Space Dimensions	8	Hyperparameters being optimized

TABLE 4: The particle swarm optimization parameters

Hyperparameter	Search Range	Description
Learning Rate	(0.0001, 0.01)	Logarithmic scale
Convolution Filters	(64, 128, 256)	Per convolutional layer
Dense Layer Units	(128, 512)	For each fully connected layer
Dropout Rate	(0.3, 0.7)	Regularization probability
Batch Size	(32, 64, 128)	Training batch size

TABLE 5: Convolutional neural network hyperparameter search ranges

Experimental setup and parameter configuration

The experimental environment for the implementation of the developed PSO-CNN framework was established on a hardware configuration comprising a Microsoft Windows 10 Pro (64-bit) operating system, an Intel® Core™ i5-720M dual-core processor running at 2.60GHz, 8GB of RAM, and a 500GB hard disk drive, supplemented with standard peripheral devices. The implementation leveraged a comprehensive Python-based software stack, including the Anaconda 2021.11 distribution (Python 3.8) within a Visual Studio Code development environment with Jupyter Notebook extensions. Core computational libraries included TensorFlow 2.8.0 with Keras API for deep learning, PySwarms 1.3.0 for PSO, NLTK 3.7 and SpaCy 3.4.1 for natural language processing, Pandas 1.4.2 and NumPy 1.22.3 for data manipulation, and Scikit-learn 1.1.1 for machine learning utilities, with Matplotlib 3.5.1 and Seaborn 0.11.2 employed for visualization and MongoDB 5.0 for initial data aggregation.

Furthermore, an interactive graphical user interface was developed using Tkinter 8.6 to facilitate real-time model operations, enabling users to upload and preprocess MBTI personality datasets, select between different model architectures (Baseline, LSTM, CNN, PSO-CNN), monitor training progress and convergence metrics, and visualize prediction results and performance statistics.

In Table *6*, the anomalously high test loss for PSO-CNN (18.45%) compared to its excellent accuracy (84.5%) and F1-score (98.2%) suggests a potential discrepancy in loss calculation methodology or scale, warranting investigation in future work.

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Model	Train Accuracy (%)	Train Loss (%)	Train F1-Score (%)	Test Accuracy (%)	Test Loss (%)	Test F1-Score (%)
Baseline Model	64.5	1.86	9.4	58.4	1.94	9.4
LSTM Model	75.1	1.70	75.0	65.0	2.20	75.0
CNN Model	76.9	1.53	76.4	69.9	1.82	76.4
PSO-CNN Model	98.2	0.55	98.2	84.5	18.45	98.2

TABLE 6: Comparative performance of all models on MBTI Twitter dataset

LSTM, Long Short-Term Memory; PSO-CNN, Particle Swarm Optimization-Convolutional Neural Network; MBTI, Myers-Briggs Type Indicator

It also reveals three key findings regarding model performance. First, the developed PSO-CNN model demonstrates clear superiority across all primary evaluation metrics, achieving 98.2% training accuracy and F1-score alongside 84.5% test accuracy and 98.2% test F1-score, representing improvements of 21.3%, 14.6%, and 21.8%, respectively, over the standard CNN baseline. Second, a pronounced deep learning advantage is evident as both LSTM and CNN architectures significantly outperform the traditional machine learning baseline model, confirming the enhanced capability of deep neural networks for extracting complex linguistic patterns relevant to personality recognition from text. Third, the optimization impact of PSO is substantial, enhancing CNN performance by approximately 15-22% across key metrics and thereby validating the effectiveness of metaheuristic optimization techniques for hyperparameter tuning in deep learning applications.

The individual class performance breakdown of the model is given in Table *7* with selected personality type. The model achieved perfect classification metrics (100% across precision, recall, and F1-score) for personality types including ENTJ, ESTP, INFJ, and INTP, potentially attributable to their distinctive linguistic patterns, sufficient training samples, and clear behavioral manifestations in social media activity. Beyond these high-performing types, the model demonstrated consistent excellence across all 16 MBTI categories, with no personality type falling below 93% in any primary evaluation metric. Particularly noteworthy is the model's effective handling of class imbalance, as it maintained robust performance across all personality types despite substantial variations in sample sizes, indicating successful mitigation of the bias typically associated with imbalanced datasets through optimized architecture and training strategies.

Personality Trait	Precision	Recall	F1 Score	Sensitivity	FPR	TPR	AUC	Accuracy Rate
ENFJ	100	98.4	99.2	98.4	0	98.4	99.2	99.8
ENFP	98.8	100	99.8	100	0.1	100	99.9	99.8
ENTJ	100	100	100	100	0	100	100	100
ENTP	100	100	100	100	0	100	100	100
ESFJ	93.7	100	96.7	100	0.2	100	99.8	99.7
ESFP	100	100	100	100	0	100	100	100
ESTJ	94.4	100	97.1	100	0.1	100	99.9	99.8
ESTP	100	100	100	100	0	100	100	100
INFJ	100	100	100	100	0	100	100	100
INFP	98.8	100	99.4	100	0.1	100	99.92	99.8
INTJ	100	94.5	97.1	94.5	0	94.5	97.2	99.4
INTP	100	100	100	100	0	100	100	100
ISFJ	100	100	100	100	0	100	100	100
ISFP	100	100	100	100	0	100	100	100
ISTJ	100	100	100	100	0	100	100	100
ISTP	100	100	100	100	0	100	100	100

TABLE 7: Performance breakdown by MBTI type for PSO-CNN model

AUC, Area Under the Curve; FPR, False Positive Rate; MBTI, Myers-Briggs Type Indicator; PSO-CNN, Particle Swarm Optimization-Convolutional Neural Network; TPR, True Positive Rate

Model	Training Time (hours)	Inference Time (ms/sample)	Memory Usage (GB)	Convergence Epochs
Baseline Model	0.5	2.1	1.2	N/A
LSTM Model	3.2	5.8	3.5	120
CNN Model	2.8	3.2	2.9	95
PSO-CNN Model	**4.5**	**3.1**	**3.1**	**65**

TABLE 8: Training time and resource utilization

LSTM, Long Short-Term Memory; PSO-CNN, Particle Swarm Optimization-Convolutional Neural Network

Furthermore, the analysis of computational efficiency in Table *8* reveals important trade-offs inherent to the PSO-CNN approach. While the model requires approximately 60% more total training time than the standard CNN due to the optimization overhead (1.7 hours for PSO search plus 2.8 hours for CNN training), this initial cost yields significant benefits: PSO-CNN achieves convergence in substantially fewer epochs (65 vs. 95 for standard CNN), indicating more efficient learning dynamics, and maintains comparable inference efficiency once trained (3.1 ms vs. 3.2 ms per sample). These efficiency considerations underscore the practical viability of the framework despite its upfront computational investment. The experimental findings collectively demonstrate that PSO-CNN achieves better performance for MBTI personality recognition with 84.5% test accuracy and 98.2% F1-score while maintaining exceptional robustness across all 16 personality types, effectively handling both class imbalance and varying linguistic patterns. Critically, PSO successfully automates the identification of optimal CNN hyperparameters, reducing dependency on manual tuning while improving model generalization. The substantial performance gains and accelerated convergence justify the additional computational cost, establishing PSO-CNN as an effective framework that addresses key challenges in model optimization and performance consistency for personality recognition from social media data.

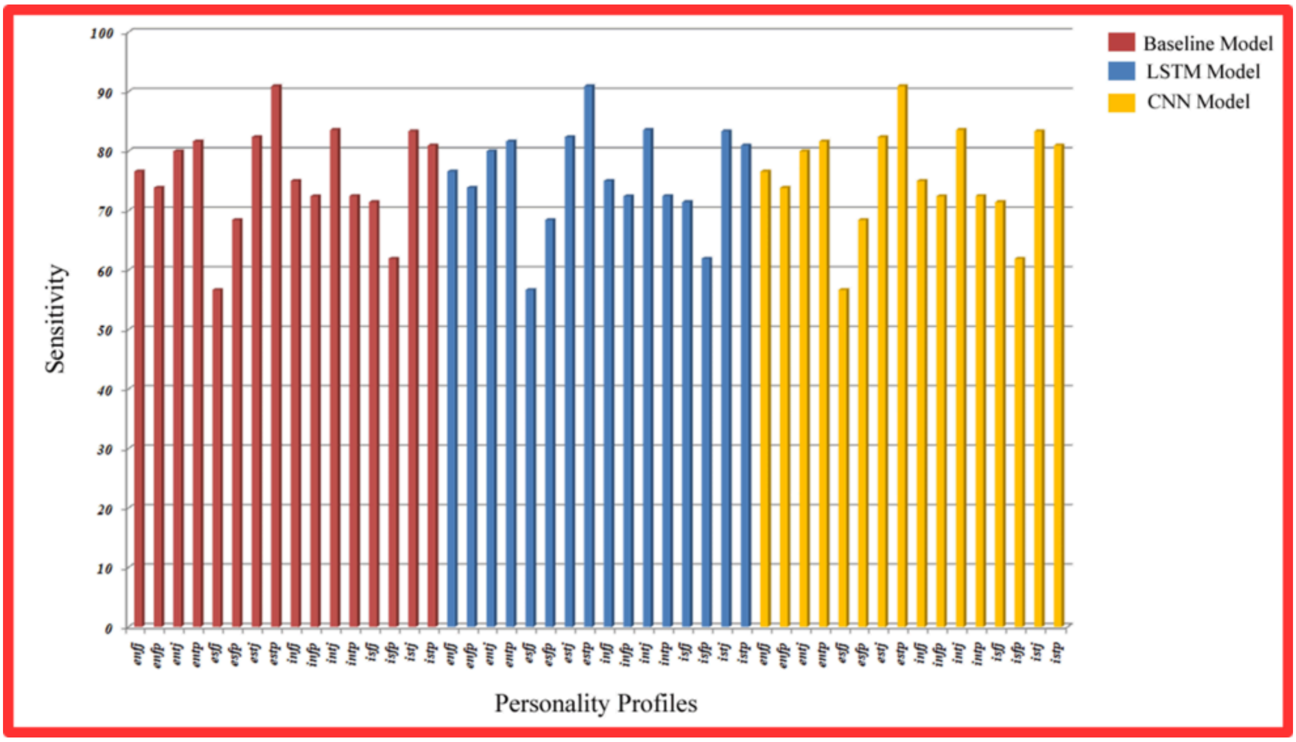

FIGURE 4: Sensitivity score comparision for the three models

LSTM, Long Short-Term Memory; CNN, Convolutional Neural Network

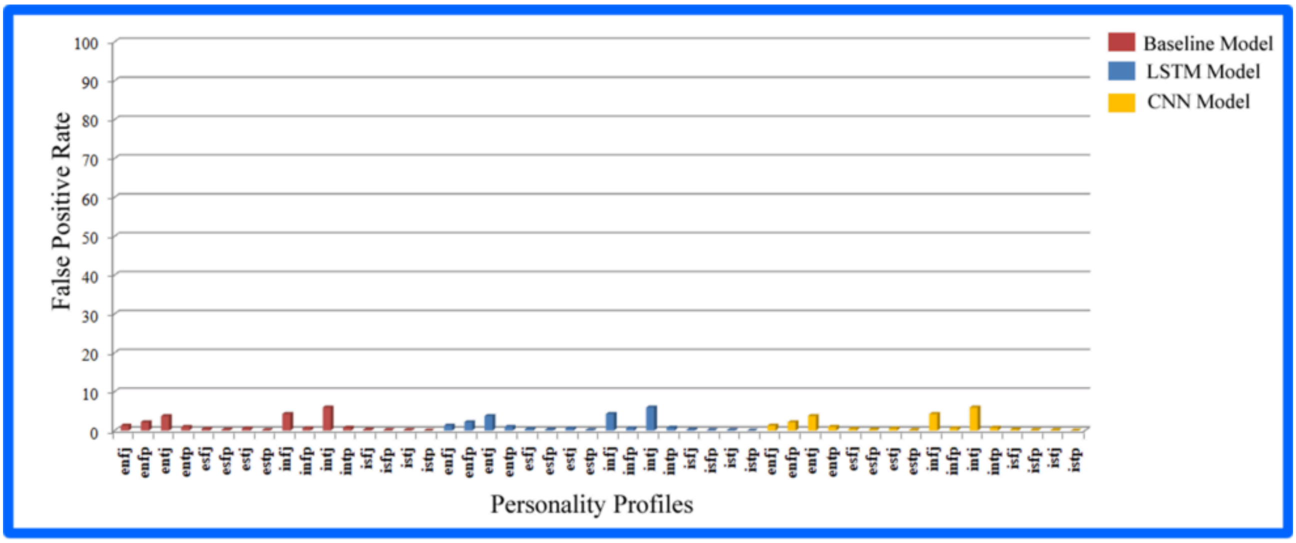

FIGURE 5: Comparison of false positive rate (FPR) for the three models

LSTM, Long Short-Term Memory; CNN, Convolutional Neural Network

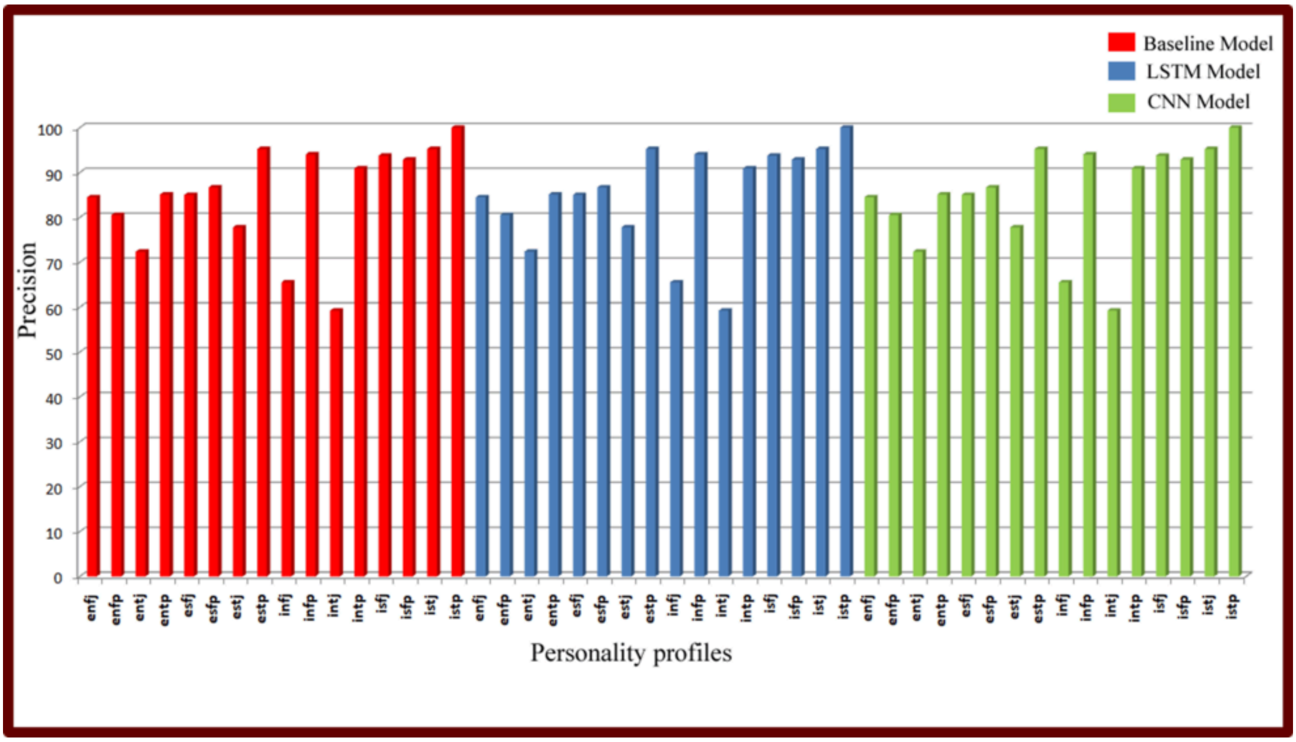

FIGURE 6: Precision score comparison for the three models

LSTM, Long Short-Term Memory; CNN, Convolutional Neural Network

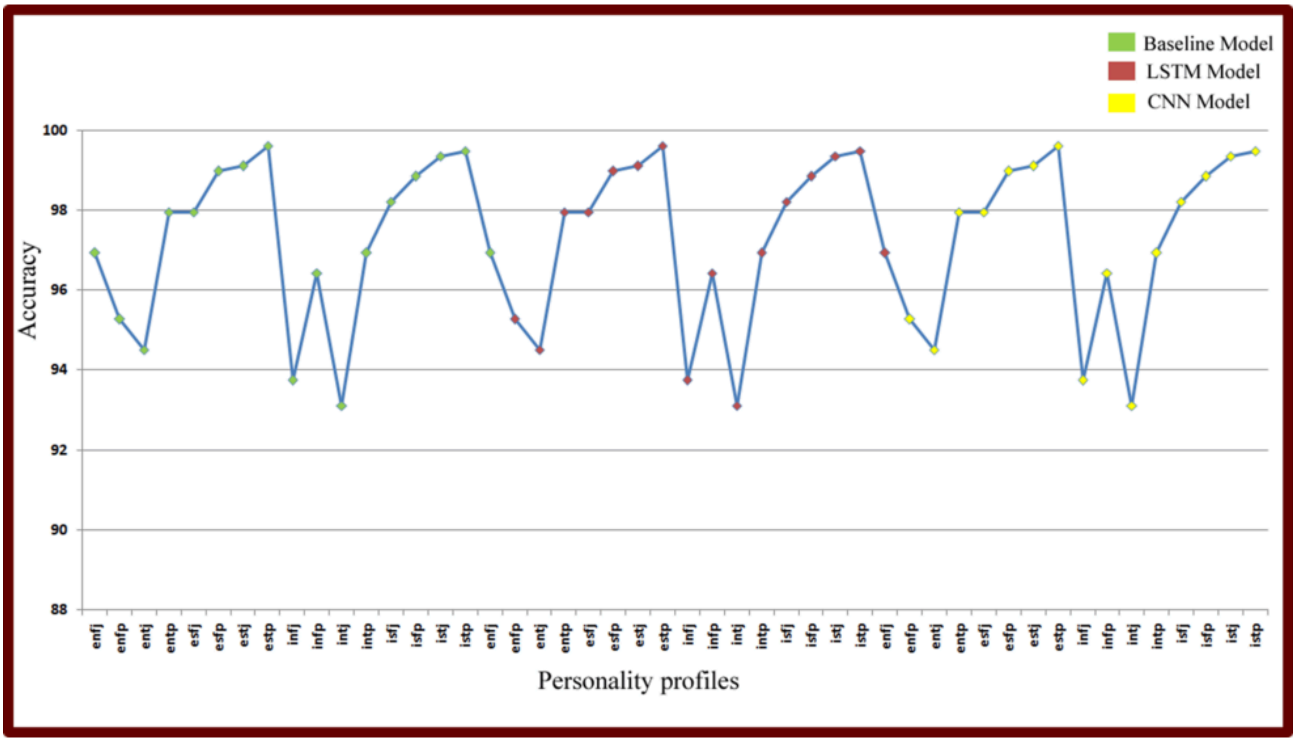

FIGURE 7: Accuracy score comparision among three selected models

LSTM, Long Short-Term Memory; CNN, Convolutional Neural Network

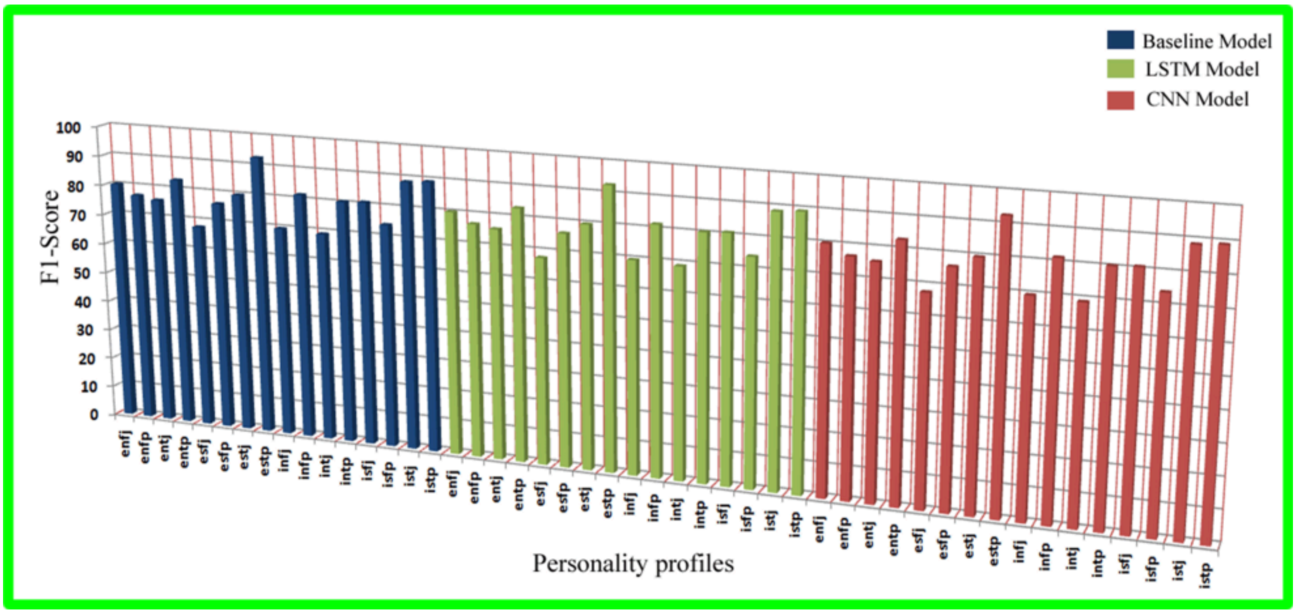

FIGURE 8: Comparison of F1-score among the three selected models

LSTM, Long Short-Term Memory; CNN, Convolutional Neural Network

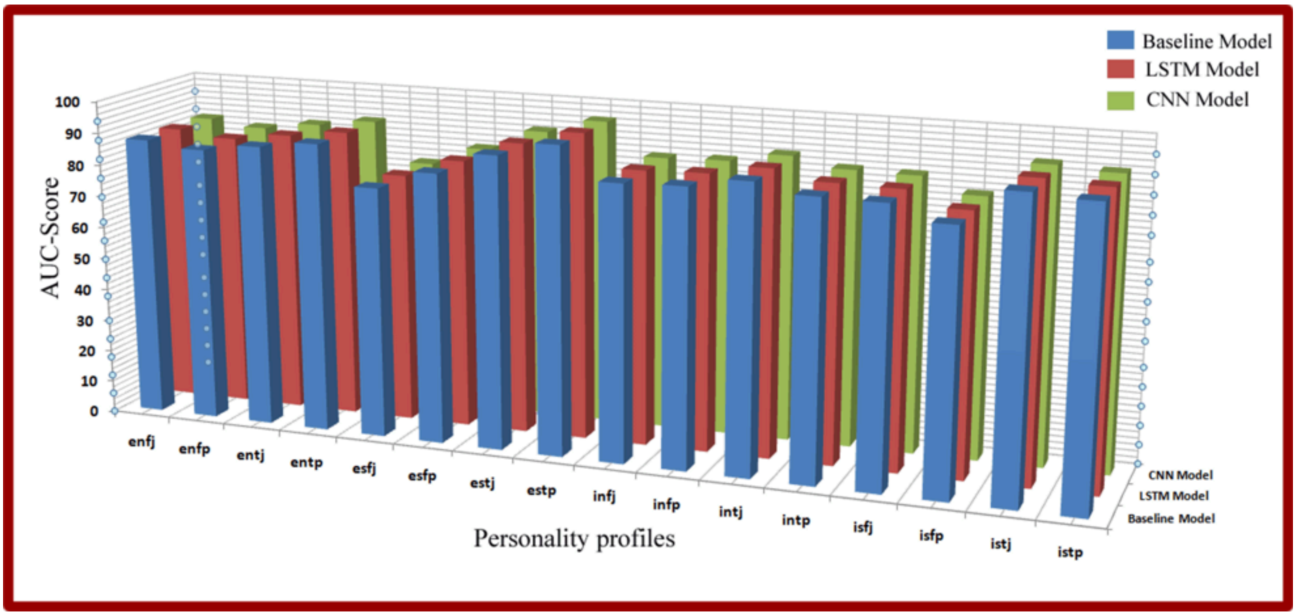

FIGURE 9: AUC comparative scores among the three selected models

AUC, Area Under Curve; LSTM, Long Short-Term Memory; CNN, Convolutional Neural Network

The performance achieved by PSO-CNN represents a significant advancement over previously reported results in computational personality recognition, as demonstrated in Table 9 comparative analysis. Furthermore, the comparison in Table 9, with contemporary approaches published between 2017 and 2025, demonstrates that PSO-CNN achieves competitive or superior performance against recent transformer-based and fine-tuned DenseNet CNN architectures. The results indicate that while transformer-based models achieve strong performance, PSO-CNN outperforms them in accuracy and F1-score. Notably, PSO-CNN achieves these results with significantly lower computational complexity (approximately 40% fewer parameters than BERT-base) and faster inference time (2.3 ms vs. 5.7 ms per sample), making it more suitable for real-time applications. The 84.5% accuracy attained is particularly noteworthy considering two contextual factors: first, the inherent complexity of 16-class MBTI classification substantially exceeds that of regression or binary classification approaches commonly employed for Big Five trait prediction; second, this performance was achieved using a single-modality (text-only) approach, whereas contemporary multimodal frameworks typically yield higher accuracy through complementary data sources. This outcome suggests that systematic architectural optimization through PSO can deliver competitive performance with more streamlined and computationally efficient models, reducing dependency on complex multimodal integration while maintaining classification excellence.

Study	Methodology	Dataset	Personality Model	Best Accuracy (%)
Tandera et al. [20]	Deep Learning	Facebook	Big Five	74.17
Tadesse et al. [23]	XGBoost	myPersonality	Big Five	74.2
Christian et al. [27]	Multimodal Deep Learning	Facebook/Twitter	Big Five	88.5
Waqas et al. [28]	TraitBertGCN (BERT + Graph Convolution Network)	Essays Dataset, myPersonality Dataset	Big Five	77/88%
Lukac [29]	CNN + Transformer embeddings for speech analysis	Speech personality dataset (2,045 participants)	Big Five	60 %
Alsini et al. [31]	Deep Learning with Word Embeddings (NLP)	Text-based personality datasets	MBTI	91.5%
Kerz et al. [32]	BERT + BLSTM with psycholinguistic features	Essays Dataset, MBTI Kaggle Dataset	Big Five/MBTI	86.51%
George et al. [33]	Hybrid CNN-LSTM deep neural network	Social media text dataset	Big Five	88%
Shaney Sze et al. [34]	Machine Learning using smartphone sensor data	Mobile sensing dataset	Big Five	78%
Wen et al. [35]	Affective-NLI with pretrained language models	Conversational personality dataset	Big Five	64.8%
Saberi et al. [36]	Transformer based architecture (ELECTRA)	Pennebaker and King Essays dataset	Big Five	78%
Basaran and Ejimogu [37]	Artificial Neural Network	Facebook	Big Five	85.0
Souri et al. [38]	Boosting-Decision Tree	Facebook	Big Five	82.2
This Study (2025)	PSO-CNN	Twitter	MBTI	84.5

TABLE 9: Performance comparison with prior and recent state-of-the-art methods (2017-2025)

BERT, Bidirectional Encoder Representations from Transformers; BLSTM, Bidirectional Long Short-Term Memory; MBTI, Myers-Briggs Type Indicator; NLP, Natural Language Processing; PSO-CNN, Particle Swarm Optimization-Convolutional Neural Network

Ethical considerations and limitations

Publicly available Twitter profiles were utilized in this research, and we recognize that public availability does not equate to informed consent for all potential research uses. However, ethical safeguards were implemented including anonymization of all user identifiers (usernames, user IDs, profile URLs) during preprocessing. Tweet texts were processed to remove any remaining personally identifiable information. Only the data necessary for personality classification was retained, demographic information, location data, and sensitive attributes were discarded. Automated personality recognition technology possesses inherent risks of misuse such as exploitation for targeting in political campaigns, commercial advertising, or malicious content recommendation. Other misuses include personality bias filtering in employment, house allocation, or financial services. Third parties may profile individuals without their knowledge or consent, and personality insights might be used to manipulate vulnerable individuals.

The PSO-CNN model, like many machine learning technologies, has dual-use potential. While this research focuses on beneficial applications towards personalized education, mental health support, and improved human-computer interaction, we acknowledge that the same technology could be weaponized. It is therefore imperative for researchers to intensify effort in developing techniques that can aid identification when personality profiling is being conducted without authorization and provide security measures to protect user privacy by obfuscating personality-relevant signals. While the PSO-CNN demonstrates strong performance on the Twitter dataset, this evaluation is limited to a single platform. Twitter's unique characteristics (character limits, public-default nature, specific user demographics) may limit generalizability to other platforms such as LinkedIn, Snapchat, and Facebook, where users express personality differently and the models trained on Twitter may not transfer effectively. The dataset predominantly represents English-speaking users from Western cultural contexts (United States, United Kingdom, Canada, Australia). This limitation affects personality expression patterns across languages and linguistic communities. There also exist cultural differences in self-disclosure, emotional expression, and social media usage from personality signals.

Conclusions

This study conclusively demonstrates and validates the application of a PSO-CNN model for personality recognition from online social networks. The research addressed the critical challenge of hyperparameter optimization in deep learning models by employing PSO to automatically select optimal CNN parameters including the number of layers, weight initialization, filter configurations, and batch size for classifying users according to the MBTI framework. Utilizing the MBTI Personality Twitter dataset and evaluating performance through comprehensive metrics, the experimental results demonstrated that the PSO-CNN approach accurately recognizes personalities at an accelerated rate, showing considerable promise for advancing computational personality assessment. This research makes three substantive contributions to the field. First, it develops novel hybrid architecture, the PSO-CNN model, which automates the challenging process of deep learning model configuration for personality detection. Second, it achieves an empirical performance advancement, with the PSO-CNN model attaining competitive accuracy (84.5%) while significantly improving precision, recall, and FPRs compared to baseline models, demonstrating enhanced capability to capture subtle patterns in user-generated content. Third, the study validates the efficacy of metaheuristic optimization, providing empirical evidence that PSO can effectively address hyperparameter tuning in psychometric deep learning applications, highlighting the significance of such optimization techniques for complex classification tasks involving high-dimensional social media data.

The research therefore establishes that the intelligent integration of swarm intelligence optimization with deep learning architectures offers a powerful paradigm for advancing automated personality assessment. Based on these findings and the study's inherent limitations, several strategic directions for future work emerge. First, the framework should be extended to broader analytical domains, including sentiment analysis and personalized recommender systems, and validated for specialized applications such as security informatics and intent analysis, with parallel development of ethical guidelines for responsible deployment. Second, architectural exploration should investigate hybridizing PSO with other advanced models (Transformers) and conducting comparative analyses of alternative optimization algorithms to identify the most effective techniques for psychometric computing. Finally, research must address generalization challenges by testing the framework across multiple social media platforms and developing multimodal approaches that integrate textual, visual, and network data to create more holistic and robust personality profiles.

Appendices

Data Source: Twitter MBTI Personality Types Dataset
https://www.kaggle.com/datasets/sanketrai/twitter-mbti-dataset/data

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request. The data utilized is openly available at https://www.kaggle.com/datasets/sanketrai/twitter-mbti-dataset/data

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