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Advanced Federated Learning with Attention-Enhanced Hybrid Deep Learning for Personality Prediction Using Handwritten Documents

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Abstract

The paper proposes an advanced federated hybrid deep learning framework combined with an attention mechanism for personality prediction based on handwriting documents. This framework utilizes CNN to extract detailed spatial features from handwriting, BiLSTM networks to capture dynamic temporal stroke features, and an attention mechanism that highlights psychologically relevant handwriting features. Differing from conventional central processing methods, which require the storage of sensitive handwriting data on the server, this method takes a step forward and uses federated learning. By learning a model over multiple distributed clients and transferring the model weights, the framework allows the privacy and security of the personal handwriting information without it being transferred to the server. The attention mechanism enhances the model accuracy and interpretability by adaptively allocating weight to each critical feature, including handwriting slant angle, spacing habits, baseline trend, and stroke continuity. According to experimental results, it achieves 94.2% accuracy, 92.8% precision, 93.1% recall, and 92.9% F1-score, which outperforms CNN (87.5%), RNN (88.3%), and centralized CNN-RNN (91.8%)-based models. Ablation study results indicated that BiLSTM captures effective sequential feature learning, the attention mechanism effectively learns discriminate features, and federated learning is capable of delivering high prediction performance along with privacy protection. In conclusion, the hybrid deep learning, attention mechanism, and federated learning combination is a feasible, explainable, and privacy-protected technique for handwriting-based personality assessment, providing a solid ground for secure psychological assessment.

Keywords: Personality Prediction, Handwritten Document Analysis, Federated Learning, Hybrid Deep Learning, Attention Mechanism, CNN, BiLSTM.

1 Introduction

Personality analysis is important in psychology, recruitment, behavioral measurement, forensic investigation systems and systems of human-computer interaction. Conventionally, psychometric questionnaires like the Myers Briggs Type Indicator and the Big Five Inventory are used to assess

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personality factors (Sharma et al., 2021). Even these approaches, though it is well endorsed, rely on self-reported answers, which can create bias, effects of social desirability, and subjective inconsistency. This has made scholars investigate other behavioral indicators such as handwriting as proxy predictors of psychological features Bhargav et al., 2025; Aouraghe et al., 2023). Stroke curvature, spacing, alignment, slant, pressure and writing rhythm are all rich structural and dynamic information found in handwritten documents. Motor behavior, cognitive patterns, and emotional tendencies can be manifested in these features, which is why handwriting can be a possible source of automated personality inference. Due to the development of artificial intelligence, deep learning models in specific cases Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) proved to be of great success when it comes to analyzing images and identifying sequences of patterns sequentially. CNNs are capable of capturing spatial handwriting details, whereas RNN-based networks, in particular, Bidirectional Long Short-Term Memory (BiLSTM) networks, acquire temporal motion of stroke sequences (Jayasree et al., 2025). The success of hybrid CNN-RNN architectures has hence become an effective way of modeling both structural and sequential characteristics of handwriting.

Regardless of such developments, the majority of available systems of personality prediction based on handwriting use centralized training systems, where sensitive handwritten information is gathered and stored in the central server (Begum et al., 2021). There are severe privacy, security, and regulatory risks associated with this type of centralization, especially when it comes to psychological or behavioral data (Drotár et al., 2016). Hacking, information violations, and misuse of personal data are the essential issues. Hence, there is the high demand of privacy-sensitive learning algorithms that can train models collaboratively without revealing raw handwritten texts (Shin et al., 2023; Hasan et al., 2024; Diaz et al., 2019). Federated Learning (FL) provides an opportunity to resolve this issue by providing decentralized-training on multiple client devices. Rather than exchanging raw data, every client trains the model locally and only sends encrypted model gradients to a central server which aggregates the model with an encryption algorithm like Federated Averaging (FedAvg) (Altwaijry & Al-Turaiki, 2021). The strategy contributes to the high level of data confidentiality and preserves the advantages of collaborative learning (Shin et al., 2022; Popli et al., 2021). Though FL has already been used in healthcare applications, finance, and mobile applications, there is a lack of research on its implementation with hybrid deep learning models in handwriting-based personality prediction (Rahim et al., 2020; Ahlawat et al., 2020). To fix the aforementioned shortcomings, this paper suggests an Advanced Federated Learning model coupled with an Attention-Enhanced Hybrid Deep Learning model in predicting personality based on handwritten documentations (Haroon & Padma, 2024; Yadav et al., 2023). The suggested architecture is a mixture of CNN-based spatial feature extraction, BiLSTM-based sequence modeling and attention mechanism highlighting psychologically discriminative handwrite parts to enhance interpretability and prediction accuracy (Liu et al., 2023). With this architecture integrated into a federated learning setup, the framework will guarantee that sensitive handwritten information is decentralized and, at the same time, competitive predictive accuracy is attained (Gagiu & Sendrescu, 2025).

Key Contributions of the Research

- The study proposes a novel hybrid model that integrates CNN for spatial handwriting feature extraction, BiLSTM for sequential pattern learning, and an attention mechanism to focus on psychologically significant handwriting segments, improving prediction accuracy and interpretability.

- The research incorporates Federated Learning (FL) into handwriting-based personality prediction, enabling decentralized model training without sharing raw handwritten data, thereby ensuring data confidentiality and compliance with privacy requirements.
- The proposed framework is systematically evaluated against standalone and centralized models, demonstrating superior accuracy, balanced precision–recall performance, scalability, and robustness across distributed handwriting datasets.

The rest of this paper is structured as follows: Section II is devoted to an in-depth survey of prior work concerning personality prediction through handwriting, hybrid deep learning models, attention mechanisms, and federated learning and points out important research opportunities. Section III introduces proposed approach: data pre-processing, an attention-based CNN-BiLSTM framework and the federated learning mechanism. Section IV presents the experimental environment, evaluation metrics, comparative studies, graphical evaluations and ablation studies. Section V discusses the results in terms of accuracy, interpretability, scalability and privacy. The last Section VI presents the conclusion and future research work.

2 Literature Review

An automatic extraction of handwriting features and mapping them to the Myers-Briggs Type Indicator personality dimensions with a deep learning-based system. A three-level architecture in which several Convolutional Neural Networks (CNNs) are used to identify fine handwriting characteristics, including slope, baseline, and spacing, and side by side with personality indicators with high accuracy (8396%). This paper demonstrates that neural classification and CNN-based feature extraction are effective in the prediction of personality using a static image of handwriting (Puttaswamy & Thillaiarasu, 2025).

The researchers designed a hybrid deep learning, which uses a Fine DenseNet to extract rich features of English handwriting followed by an Adaptive Multidimensional LSTM-CTC sequence model to improve the process of classifying personality traits. Combining such fine connectivity and sequence modeling allowed the correspondence of the features of multidimensional and complex handwriting, which led to very high accuracy (97.6%). Although it is based on hybrid structures, this paper highlights the significance of high-level feature hierarchies and time modeling in behavior prediction based on handwriting Rahim et al., (2024)

The proposed a CNNBiLSTM hybrid scheme to examine handwriting with the purpose of personal identification, which involves a wide range of features extraction and sequential modeling deep. Despite the lack of emphasis on personality, but an emphasis on identity, the work shows how the synergistic role of spatial and sequence learning can be effective in discriminative identification of handwritten examples. Their hybrid design outperformed individual CNN or RNN models in terms of classification performance, and is relevant to personality-motivated handwriting tasks, where temporal dependencies are important (Raveendhran & Krishnan, 2025).

The hybrid architecture of deep learning which predicts personality traits using behavioral measurements (not handwritten) and combines two streams of features and deep networks. Although it is not purely handwriting-related, this new paper highlights the direction of hybrid systems and the development of complex feature combinations (such as attention mechanisms in such areas) to enhance interpretability and prediction accuracy in the face of privacy limitations, suggesting a wider applicability of federated, multimodal personality inference systems (Srivastava et al., 2021).

To investigate spatial attention and multi-scale fusion in order to improve the text-independent identification of writers. Their deep learning model highlights that attention mechanisms is able to concentrate on discriminative regions of handwriting, which is beneficial in feature representation and inter-writer differentiation. Although it is not a personality study, as such, their methodology shows how attention may be used to enhance model sensitivity to characteristic handwriting patterns a concept that can be explicitly applied to attention-enhanced models of personality prediction (Sree et al., 2024).

This research explored extraction and modeling of handwriting features in as far as prediction of personality traits is concerned. The study was aimed at measuring structural handwriting characteristics including slant, variance of the baseline, distance among the strokes, and dynamic of strokes through the latest pattern recognition methods. This work, by showing that machine classifiers can effectively make inferences of various dimensions of personality with encouraging levels of accuracy when trained on labeled data on handwriting, identified that computational handwriting analysis remains a viable psychological assessment instrument than graphological, and thus proved that computational handwriting analysis was valid as a psychological assessment instrument (Biswas et al., 2025).

Table 1: Comparative analysis of recent deep learning approaches for handwriting-based personality prediction

Ref	Methodology	Dataset / Simulation Environment	Research gap
Puttaswamy & Thillaiarasu, (2025)	Multi-level deep learning architecture using multiple CNNs for automatic extraction of handwriting features mapped to MBTI personality traits.	Static handwritten image dataset labeled dataset.	Focused only on static handwriting images; lacks sequential modeling and privacy-preserving federated framework.
Rahim et al., (2024)	Hybrid Fine DenseNet for spatial feature extraction combined with Adaptive Multidimensional LSTM-CTC for sequential modeling.	English handwriting dataset from non-native writers annotated with personality traits.	Centralized training framework; no integration of privacy-aware or federated learning mechanisms.
Raveendhran & Krishnan, (2025)	CNN–BiLSTM hybrid model for spatial and temporal handwriting feature learning.	Handwriting dataset for writer identification experiments.	Focused on writer identification rather than personality prediction; lacks psychological trait mapping and privacy considerations.
Srivastava et al., (2021)	Hybrid deep learning framework integrating multiple behavioral feature streams with deep neural networks.	Behavioral (non-handwriting) personality datasets under supervised learning setup.	Not handwriting-specific; no validation on handwriting data and no federated privacy-preserving implementation.
Sree et al., (2024)	Deep learning model using spatial attention and multi-scale fusion for feature enhancement.	Text-independent handwriting dataset for writer identification.	Applied to writer identification; lacks personality trait classification and decentralized training mechanisms.
Biswas et al., (2025)	Supervised machine learning with structural handwriting feature extraction (slant, spacing, baseline variance, stroke dynamics).	Labeled handwriting dataset for personality trait prediction.	Relies on handcrafted features; limited deep hybrid modeling and no privacy-preserving framework.
Méndez et al., (2023)	Multi-task learning framework with shared feature extractors and task-specific personality classification layers.	Handwriting dataset labeled with multiple personality dimensions.	Centralized deep learning; does not address data privacy, scalability, or federated optimization.

This Study suggested a multi-task learning model, which simultaneously optimized handwriting feature representation at the same time as classifying personality traits. The model effectively learned task-specific and shared feature extractors to the multiple personality dimensions using a single model. It was found through experimental data that this strategy enhanced classification through single-task models, and showed that multi-objective deep learning can be considered an effective method to learn the complex handwriting behavior patterns important to personality inference (Méndez et al., 2023).

In table 1 provides a comparison of recent literature on handwriting-based personality prediction and its related deep learning techniques. Significant improvements have been witnessed in the implementation of CNN, hybrid CNN-RNN, attention mechanisms, and multi-task learning in the literature on feature extraction and classification. The majority of the works use centralized training and do not consider any privacy mechanisms in their models. The majority of works are primarily focused on writer identification rather than personality prediction and use handcrafted features or non-handwriting behavioral datasets for personality prediction. These limitations indicate the necessity for an attention-enhanced hybrid deep learning model combined with federated learning for performing accurate, scalable, and privacy-preserving personality prediction from handwritten documents.

Research Gap

The gap in research in the current study is that there is a heavy reliance on centralized training, only one type of feature is used either spatial or sequential, and there are no mechanisms that ensure the privacy of the data. Furthermore, past researches do not incorporate attention mechanism to point out important traits of handwriting from a psychological perspective in federated learning.

3 Methodology

Overall Architecture for the Proposed Methodology

In figure 1 shows the high-level pipeline for predicting the personality of the author of a handwritten document by adopting the federated learning approach supported by an attention-based hybrid deep learning system. The handwritten data, which is distributed across multiple clients, are locally preprocessed, consisting of operations like scanning, denoising, binarization, skew correction, resizing, and segmentation of the data.

Clients train a local hybrid deep learning model with both CNN and Transformer networks for learning spatial and sequential handwriting features. Attention layers emphasize relevant features, which are fed into a fully connected network to predict Big Five personality traits. The updated global model is redeployed to clients for continued learning. Features of federated learning such as attention-based averaging, client sampling, communication compression, privacy protection, and adaptive personalization improve model performance. The system produces Big Five personality scores and explanations, measured by MAE, RMSE, CCC, and cross-domain generalization performance. Uses are in human resources, education, counseling, psychology, and forensic and behavior analysis domains.

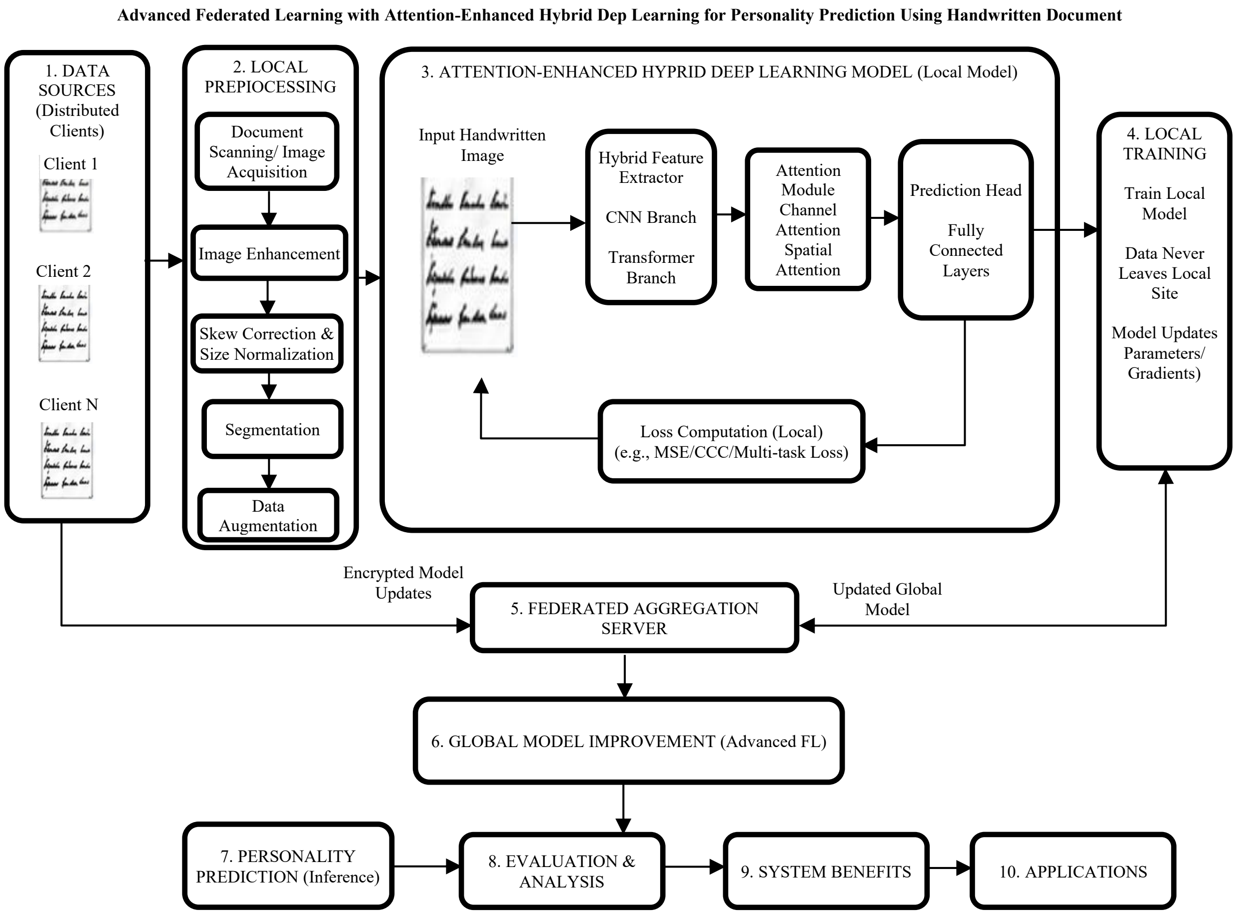

Figure 1: Overall architecture for the proposed methodology

Working Principle for Federated Learning for Personality Prediction

The FedML framework for federated learning is described in figure 2. HTTP and TCP are communication protocols to enable communication between the FedML server and FedML-mobile/FedML-IoT devices. Mobile devices like Android and iOS, also NVIDIA IoTs and Raspberry Pi, can participate in FL. It offers a high-level API that interacts with models and data. Supporting popular FL algorithms like FedAvg, FedOpt, FedNova, FedNAS, and distributed/vertical learning scenarios. FedML Core API implements distributed communication, safety, and privacy. The training layer is composed of workers, coordinators, learning algorithms, and optimizers that train the local models using PyTorch on mobile devices without sharing data.

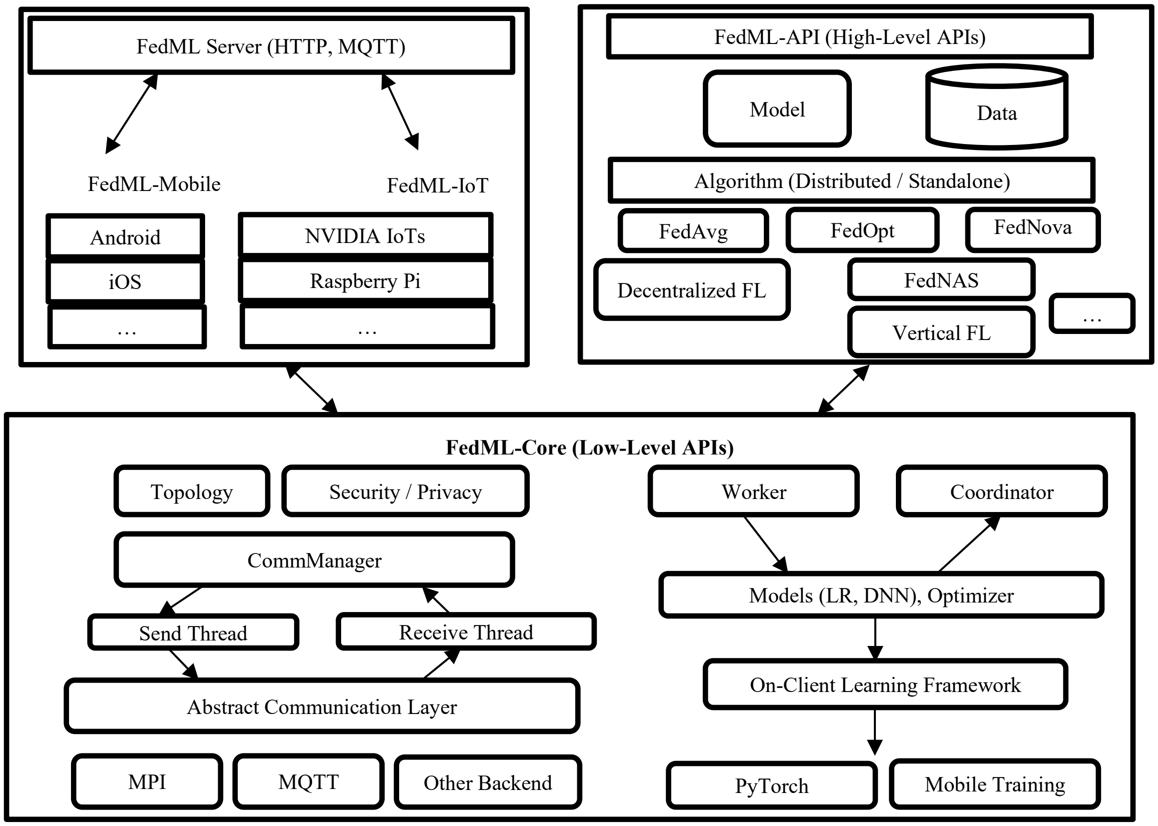

Figure 2: Working principle for federated learning for personality prediction

At its core, federated learning can be understood as a distributed optimization problem that trains a global model without centralizing the data. Formally, suppose there are K clients indexed by $K\epsilon\{1,2,\dots,K\}$, Where $n=\sum_{k=1}^{k} n_k$. Denote the model parameters (e.g., the weights of a neural network) by $w\epsilon R^d$. The goal of federated learning is to minimize a global empirical risk objective that aggregates the losses over all clients' data, without ever directly pooling those data together. This objective can be written as

$$min_{w\epsilon R^d} F(w)=\sum_{k=1}^{k}\frac{n_k}{n}F_k(w) \quad (1)$$

From the above equation (1) $F_k(w)$ should represents the local objective for client k. The local objective should be defined as empitrical risk among the client k dataset.

$$F_k(W)=\frac{1}{n_k}\sum_{(x_t,y_{t)\in D_k}} l(w,x_t,y_t) \quad (2)$$

From the above equation (2) describes the $l(w,x_t,y_t)$ should represents the data sample x_i,y_i with the simple terms of $F_k(w)$ should be measured as the w fit the data of client k and $F(w)$. The model parameter should perform the collective data through clients without requiring the client to send the raw dat to the server.

A standard method for solving this federated optimization problem is called Federated Averaging, or FedAvg. FedAvg is a process that happens in repeated rounds where the server and a group of clients, usually a part of all clients, communicate at the same time. Each round starts with the server sending the current model to the clients at the beginning of each round t.

$$w^{t+1} = \sum_{k \epsilon S_t} \frac{n_k}{\sum_{j \epsilon S_t} n_j} w_k^t \qquad (3)$$

Equation (3) weights clients by the size of their dataset during the aggregation. In each round ($t = 0, 1, 2, \ldots$), FedAvg approximates centralized SGD by averaging the local models to decrease communication cost and points out some practical issues such as data heterogeneity, heterogeneous devices, network constraints, privacy requirements, etc.

Horizontal Federated Learning (HFL)

In horizontal federated learning, all the clients involved share the same set of features and the same set of labels. However, each client has its own group of data samples. In a formal way, the feature space and label space are the same across all clients.

$$X_1 = X_2 = \cdots \ldots . -X_k \qquad y_1 = Y_2 = \cdots \ldots y_k \qquad (4)$$

From the above equation (4) describes the sample index spaces,

$$j_k \cap j_j = \emptyset \qquad \forall k \neq j \qquad (5)$$

As stated in equation (5), clients are distributed horizontally over the global dataset; each client contains distinct data samples but a common feature and label space. One of the representative examples is training a language model over clients distributed on multiple user devices. All the devices will utilize the same feature space and task prediction, and each device provides a separate local sample set.

Vertical Federated Learning (VFL)

In vertical federated learning, all clients work with the same set of data samples, but each has access to different feature subsets. Officially, every client uses the same set of sample indexes as shown in equation (6).

$$J_1 = j_2 = \cdots \ldots \ldots . = j_k \qquad (6)$$

The feature among the spaces is distinct and complementary

$$x_1 \neq x_2 \neq \cdots \ldots \ldots X_k \qquad (7)$$

From equation (7) above, each client sees only part of the feature representation for the same entities. The training process usually involves optimizing together across the combined feature space, which is made possible through methods like secure aggregation, split learning, or other cryptographic techniques.

Federated Transfer Learning is used to handle the general scenario where clients have differences in both the feature spaces and the sample index spaces.

$$x_k \neq x_f \quad and\ j_k \cap j_l \neq \emptyset, \forall k \neq j \qquad (8)$$

From the above equation (8) FTL exploits partial overlap in label semantics, feature representations, or auxiliary knowledge to enable cross-client knowledge transfer despite minimal data alignment.

Attention-Enhanced Hybrid Deep Learning for Personality Prediction

The hybrid deep learning process for text-based emotion detection is presented in figure 3. Pre-processing of the raw text data is done to represent the text in dense vectors through Word2Vec embeddings. Model parameters are trained with the Oscillating Chaotic Sunflower Optimisation (OCSFO) algorithm. Emotion classification is done with an HA-LSTM classifier. Performance metrics used are accuracy, precision, recall, F1-score, and AUC.

Textual detection using HA-LSTM

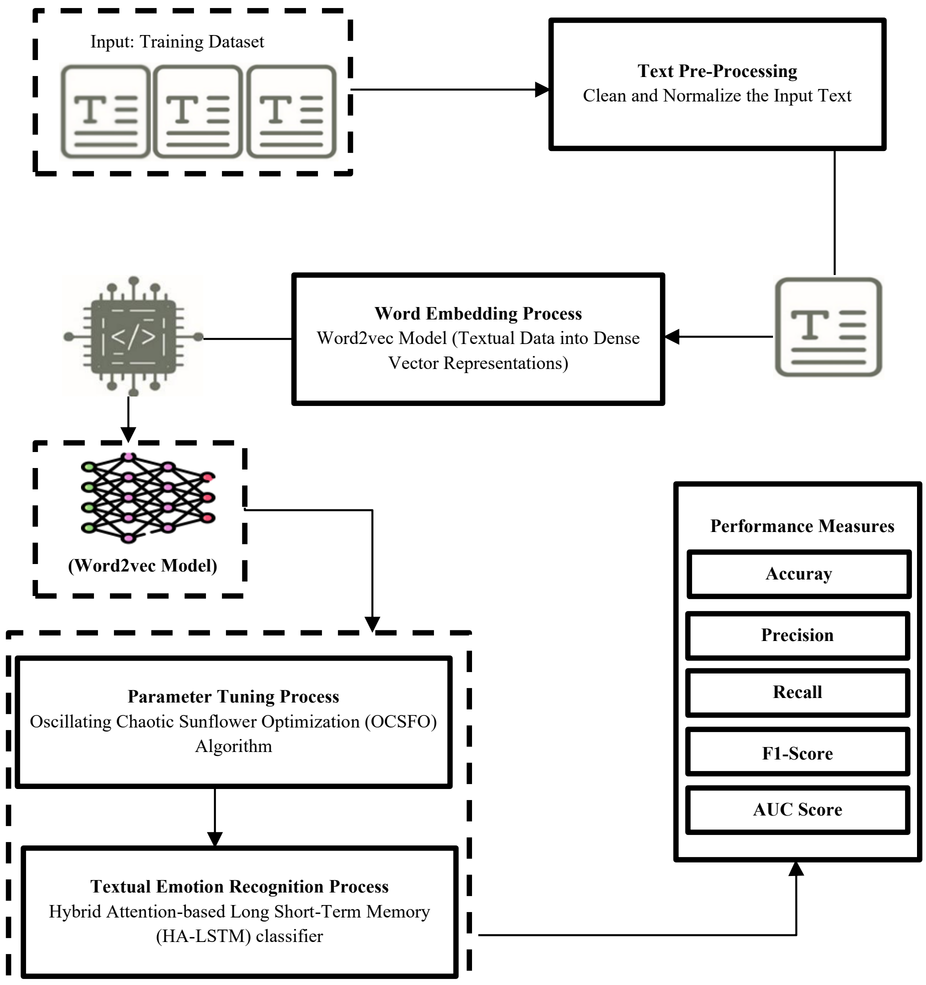

Figure 3: Attention-enhanced hybrid deep learning for personality prediction

Furthermore, the HA-LSTM classifier is implemented for effective recognition in text32. The reason behind choosing this classifier is that it includes both the strengths of the LSTM network and attention mechanism (AM). Since the LSTM network can be applied for sequence processing and has long memory capability, it can be used for capturing the contextual meaning within an emotion expression. The inclusion of the AM in the LSTM network helps it focus on those textual parts which hold more relevance for the task, and thus increase the sensitivity to emotions. In comparison to models such as the CNN and RNN model, the HA-LSTM is more efficient in recognizing emotions that require context comprehension. Furthermore, this classifier increases the interpretability of the model and makes it more effectual in emotion recognition.

LSTMs belong to an advanced class of RNNs that have been developed specifically for learning long-term dependencies in sequential data. The main advantage of LSTMs is their ability to store information for a longer period of time due to their memory cells controlled by three gating systems: the input gate, the forget gate, and the output gate.

$$f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right) \quad (9)$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (10)$$

$$C_t = \tanh(W_c.[h_{t-1}, x_t] + b_c \quad (11)$$

$$C_t = f_t * C_{t-1} + i_t * C_t \quad (12)$$

$$O_t = \sigma(W_0.[h_{t-1}, X_t] + b_o \quad (13)$$

$$h_t = o_t * \tanh(C_t) \quad (14)$$

From the above equation (9), (10), (11), (12), (13) and (14) Here, denotes the sigmoid activation function, $tanh$ is the hyperbolic tangent function, and $*$ represents element-wise multiplication. The vector h_{t-1}, x_tconcatenates the previous hidden state (HS) and the current input.

Multi Head Self Attention Module

MHSA is used to improve this ability even more. It lets the model learn from several different subspaces at the same time, giving it a better overall understanding of the input data. Each head works on the input in a different way, picking up on different connections throughout the sequence. The multi-head attention process is shown in equation (15).

$$MultiHead(Q, K, V) = Concat(head_1, \dots \dots Head_h)W^0, Head_i = Attention\left(QW_i^Q, KW_i^k, VW_i^y\right) \quad (15)$$

From the above equation (15) describesV, Q, K followed by matrices $W_i^Q, W_i^k, W_i^y and\, W^o$ are matrices of the learnable parameters, and h depicts attention, headcounts. Q, K, V are the query, key, and value matrices derived from the input, and QW_i^Q, KW_i^k, VW_i^y represents the learnable weight matrices for each attention module.

Data Acquisition and Preprocessing

This framework aims to gather handwritten samples from universities, psychological test centers, and pen-tablet computers and personality labels via standardized psychological tests. The data after anonymization and approval is pre-processed by grayscale conversion, noise reduction, normalization, resizing, and segmentation. Dynamic features (stroke sequence, pen pressure, and writing speed) would be collected if available. Rotate, scale, and elastic distortion data augmentation methods are used for better generalization. The pre-processed data is allocated to different clients and trained via private-keeping federated learning without revealing the original data.

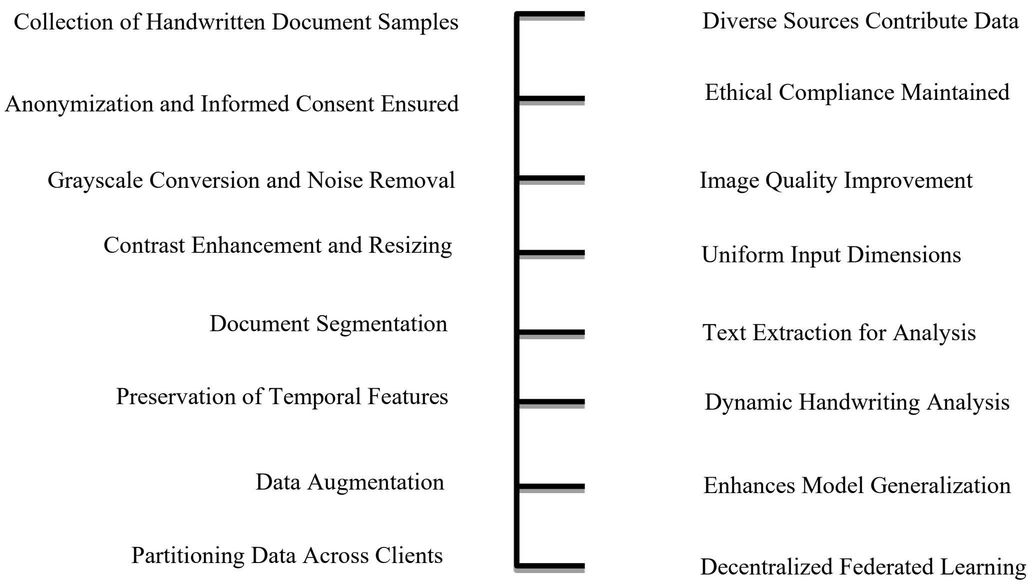

Figure 4: Workflow of handwritten data preprocessing and federated data preparation

In figure 4 shows the data flow process for handwritten data preparation in the federated personality prediction framework. This begins with the data collection, anonymization, and consent phase. After collection, the data will pass through preprocessing, including greyscaling, noise reduction, contrast enhancement, resizing, and document segmentation. The dynamic nature of the handwritten data can be preserved via retention of temporal handwriting features; the data will also be enhanced by the application of augmentation. This then allows for distribution to numerous clients and facilitates a privacy-preserving federated learning process.

Hybrid Deep Learning Model Design

The core predictive model is modelled as an attention enhanced hybrid deep learning framework that consists of Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks. CNN component obtains the hierarchical spatial representations of handwritten images in terms of stroke curvature, slant angle, and spacing pattern, as well as baseline alignment. Several convolutional layers gradually acquire low-level edge features and high-level structure writing styles. The resulting feature maps are reformatted to sequential representations and sent through a BiLSTM layer, which models both forward and backward temporal relationships and writing dynamics. To enhance the interpretability and classification accuracy, a soft attention mechanism is also added to emphasize on more psychologically significant areas of handwriting by weighting them more heavily. The last fully connected layers transform the learned representations into the categories of personality traits with the help of the softmax or sigmoid activation functions. Adam optimizer is used to optimize the model with the cross-entropy loss to get steady convergence.

In figure 5 represents a step-by-step deep learning workflow that is set to process data by sequentially identifying and refining meaningful patterns. Spatial features are first generated to store structural information and finally reshaped so as to be subjected to sequential modeling. It learns temporal dependencies to learn how things change with time after which an attention mechanism is employed to show the most useful features. These sophisticated representations are mapped to personality traits to make predictions or classifications and this process is optimized to get better results by continuous feedback. The repetitive procedure guarantees proper learning of both spatial and temporal attributes resulting in more credible and dependable inferences of personality traits.

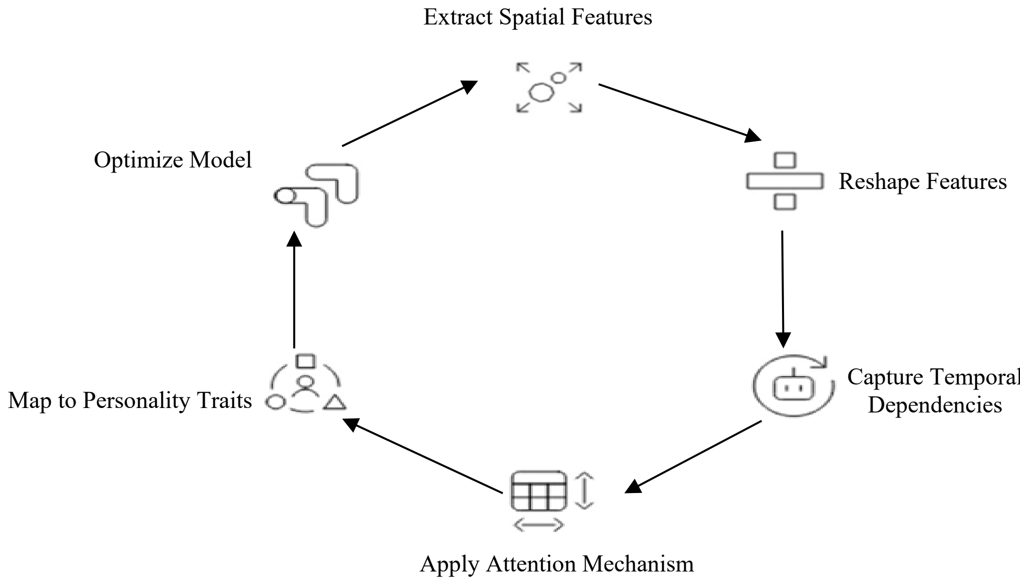

Figure 5: Cyclic deep learning framework for spatial–temporal feature extraction and personality trait prediction

Federated Learning-Based Privacy-Preserving Training

The proposed hybrid model is implemented within the framework of federated learning to maintain privacy regarding centralized data storage. A global model is broadcast to various clients, which conduct local training with handwritten digits without transmitting raw data. The model update is then transmitted to the server in an encrypted form, and the model update is aggregated using the FedAvg algorithm to update the global model. This procedure iterates until convergence. Moreover, differential privacy and secure aggregation can be applied to improve data privacy.

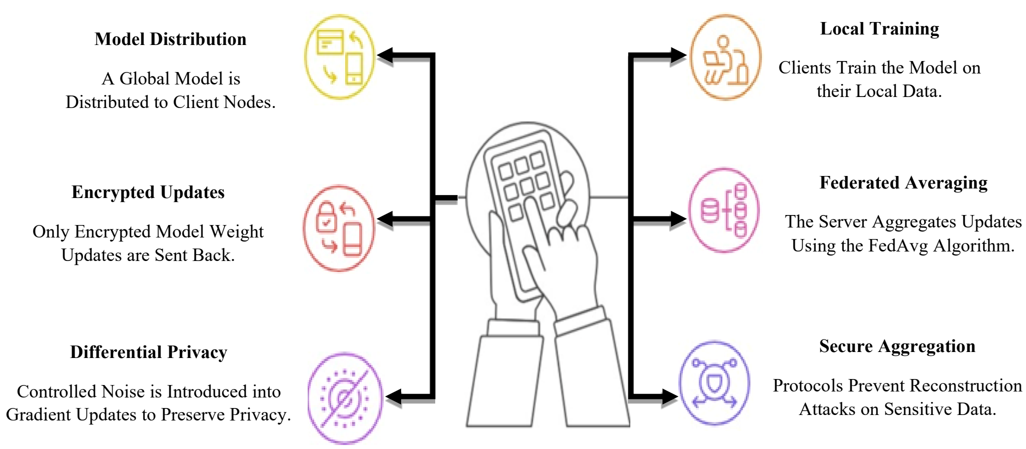

Figure 6: Privacy-preserving federated learning workflow for secure collaborative model training

The general federated learning process is shown in figure 6. A global model is sent from the server to clients for local training by data locally saved on clients. The encrypted model updates (instead of original data) are sent back to the server. The Paillier cryptosystem is employed for encryption, and differential privacy can add noise for privacy. All encrypted updates are aggregated in secure aggregation, and the FedAvg algorithm is applied by the server.

Cross-Entropy Loss Function (Classification Loss)

$$L = -\sum_{i=1}^{c} yilog(yi) \quad (16)$$

This equation (16) represents the cross-entropy loss used to train the hybrid CNN–BiLSTM model. Here, $Yi$is the true label, is the predicted probability for class iii, and CCC is the number of personality classes. The loss shows how much the predicted values differ from the actual ones. Making this loss as small as possible during training helps make the classification of personality traits more accurate.

Federated Averaging (FedAvg) Update Rule

$$W^{(t+1)} = \sum_{k=1}^{k} \frac{n^k}{n} W_k^{(t)} \quad (17)$$

This equation (17) represents the federated averaging process. Here, $Wk(t)$ is the model weight from client k,nk is the number of samples at client k, n is the total number of samples across all clients, and K is the total number of clients. The server aggregates local model updates to form the new global model without accessing raw handwritten data, ensuring privacy preservation. Before aggregation, each client update is further protected using differential privacy (noise injection) and secure aggregation based on the Paillier Cryptosystem to ensure that individual updates remain confidential.

Proposed Algorithm

Algorithm: Federated Hybrid CNN–BiLSTM for Personality Prediction

1.Distributed handwriting datasets D1, D2, DK
2. For each communication round t = 1 to T do
3. Send global model W to all clients
4. For each client k = 1 to K (in parallel) do
5. Load local dataset Dk
6. Wk = W
7. For epoch = 1 to E do
8. Train CNN–BiLSTM model on Dk
9. Compute loss using Cross-Entropy
10. Update local weights Wk
11. End For
12. Send updated weights Wk to server
13. End For
14. Aggregate client weights using FedAvg:
*15. W = Σ (nk / n) * Wk*
16. End For
*17. Return final global model W**

The algorithm starts with the initialization of global hybrid CNN-BiLSTM model at the main server. The global model is communicated with all clients involved in every communication round. Every client is training the model locally on its handwritten dataset with a fixed number of epochs and training the model weights with cross-entropy loss. Clients do not send raw handwriting data but only send the new model weights to the server. These weights are then summed (based on Federated Averaging (FedAvg) mechanism) by the server to produce a better global model. The process is repeated until the convergence of the model. The end result is a trained global model that is able to predict personality traits without invading data privacy.

4 Experimental Results

Experimental Setup, Handwritten Personality Dataset, and Parameter Initialization

The experiments were conducted using a custom-collected Handwritten Personality Dataset (HPD), obtained from educational institutions and digital pen-tablet platforms to assess the efficiency of the developed Attention-Enhanced Hybrid CNNBiLSTM model that is combined with Federated Learning (FL) in predicting personality using handwritten documents. The collection of the handwriting data was done using sources of distribution such as institutions of learning and digital pen-tablet sites. Every sample was coded with established personality assessment models including the Big Five and MBTI traits. The processing methods that were executed on all handwritten images were grayscale conversion, noise filtering, normalization, and segmentation. The data augmentation techniques such as rotation, scaling and elastic distortion were used to enhance generalization. In the case of federated training, the data was shared between a number of simulated clients to simulate decentralized learning environments. The hybrid model was made up of three convolutional layers (32, 64 and 128 filters), then a Bidirectional LSTM layer that had 128 hidden units with a soft attention mechanism. The model had 32 as the batch size and was trained on the Adam optimizer at a learning rate of 0.001. Every client completed 50 local epochs at once communication round and 20 federated communication rounds were carried out. The optimization objective was cross-entropy loss. The table 2 below outlines the experimental setup that was used to test the proposed Attention-Enhanced Federated Hybrid Deep Learning model. It entails the properties of datasets, preprocessing, architecture, federated learning, and performance assessment metrics in the form of evaluation metrics.

Table 2: Experimental setup, dataset, and model parameter initialization

Parameter	Value / Description
Data Sources	Educational institutions, digital pen-tablet datasets
Personality Labels	Big Five traits and MBTI personality types
Data Type	Static handwritten images and dynamic stroke sequences
Preprocessing Steps	Grayscale conversion, noise removal, normalization, segmentation
Data Augmentation	Rotation, scaling, elastic distortion
Number of Clients (Federated Setup)	5 simulated clients
CNN Architecture	3 Convolution layers (32, 64, 128 filters)
Sequential Layer	Bidirectional LSTM (128 hidden units)
Attention Mechanism	Soft attention layer
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Local Epochs per Client	50
Communication Rounds	20
Loss Function	Cross-Entropy Loss
Federated Aggregation Method	Federated Averaging (FedAvg)
Evaluation Metrics	Accuracy, Precision, Recall, F1-score

Performance Metrics

The performance of the proposed federated hybrid CNN–BiLSTM model is evaluated using standard classification metrics derived from the confusion matrix components:

In equation (18) shows that accuracy measures how correct the model is by looking at the percentage of predictions that were right out of all the predictions made.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (18)$$

Precision, equation (19), is defined as the ratio of all correctly identified positive predictions to all actual positive instances. This parameter is capable of diminishing false-positive prediction and gives the accurate estimation for prediction performance. Precision is applied to evaluate the different models in this paper.

$$Precision= \frac{TP}{TP+FP} \quad (19)$$

In equation (20) shows Recall measures how many actual positive cases were correctly detected. High recall ensures that arrhythmias are not missed.

$$\text{The Recall} = \frac{TP}{TP+FN} \quad (20)$$

In equation (21) shows F1-score is the harmonic mean of precision and recall, providing a single metric for imbalanced datasets.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (21)$$

These metrics collectively provide a comprehensive evaluation of the predictive performance, robustness, and reliability of the proposed personality prediction model.

Performance Evaluation

The presented attention-enhanced hybrid CNN-BiLSTM model is assessed through its performance metrics, including accuracy, precision, recall and F1-score, and the metrics achieved with a basic CNN, RNN, and a centralised CNN-RNN. These are used not only to analyse the prediction ability but also to analyse its reliability, where precision plays a vital role in validating the correct classification of personality traits and ensuring minimal false positives. Furthermore, accuracy loss of the federated model along with the privacy retention ability is analysed to determine the model has not suffered substantially in terms of prediction accuracy due to decentralised learning.

Table 3: Performance evaluation of personality prediction models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN Only	87.50	85.80	86.20	86.00
RNN Only	88.30	86.50	87.00	86.70
CNN–RNN (Centralized)	91.80	90.50	90.80	90.60
CNN–BiLSTM–Attention (Federated) – Proposed	94.20	92.80	93.10	92.90

In table 3 compares attention-enhanced federated hybrid CNN-BiLSTM model with standalone CNN, RNN, and centralized CNN-RNN models. In contrast, standalone CNN and RNN had very low performance, and the centralized CNN-RNN with both spatial and sequential features reached an accuracy of 91.8%. Federated CNN-RNN with attention has outperformed and reached an accuracy of 94.2%, precision of 92.8%, recall of 93.1%, and F1-score of 92.9%. From the above experiment, it can be deduced that attention mechanisms lead to highly discriminative feature learning, and federated training techniques ensure privacy of data without sacrificing predictive capability to have better robustness and generalization.

Evaluation Metrics of Personality Prediction Models

Table 4: Evaluation metrics of personality prediction models

Model	Matthews Correlation Coefficient (MCC)	Cohen's Kappa (Î°)	AUC-ROC	Balanced Accuracy (%)	Hamming Loss	Macro F1 (%)	Weighted F1 (%)
CNN Only	0.74	0.72	0.91	86.5	0.12	85.9	86
RNN Only	0.76	0.75	0.92	87	0.11	86.4	86.7
CNN-RNN (Centralized)	0.84	0.82	0.96	91.2	0.08	90.7	90.6
CNN-BiLSTM-Attention (Federated)	0.89	0.87	0.98	93.9	0.06	92.8	92.9

The detailed performance analysis results using multiple state-of-the-art metrics are reported in table 4 and figure 7 of the proposed CNN-BiLSTM-Attention with FL model. This shows that the proposed CNN-Bilstm-Attention with FL performs the best among all compared techniques, with an accuracy of 93.9%, MCC of 0.89, Cohen's Kappa of 0.87, and AUC-ROC of 0.98 in predicting ability and discrimination. The model achieves a minimum Hamming loss of 0.06 and a higher macro F1 of 92.8% and weighted F1 of 92.9%.

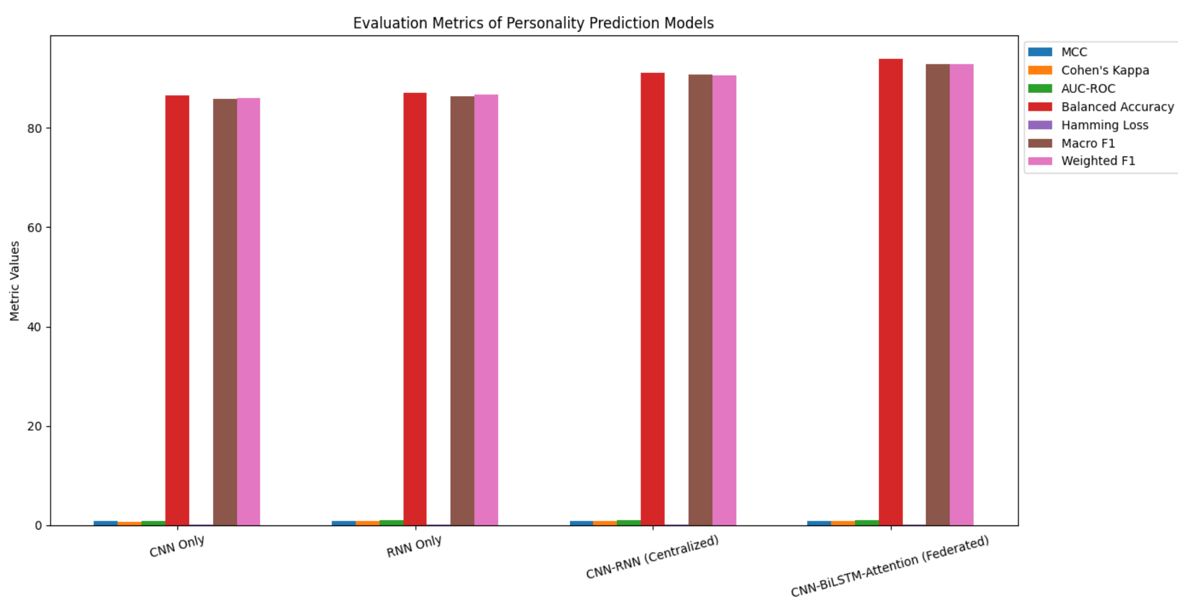

Figure 7: Evaluation metrics of personality prediction models

Graphical Analysis of Results

The analysis of the experimental outcomes in the form of the graph that will offer a clear visual comparison of the proposed model and the base approaches. Moreover, the training and validation loss curves of federated communication rounds are determined to determine the model stability and convergence behavior. The graphical illustration assists in discerning the performance patterns, learning effectiveness and how attention mechanisms and federated learning effect the comprehensive predictive potential. The visual analysis allows proving the robustness, scalability and consistency of the proposed Attention-Enhanced Federated Hybrid model.

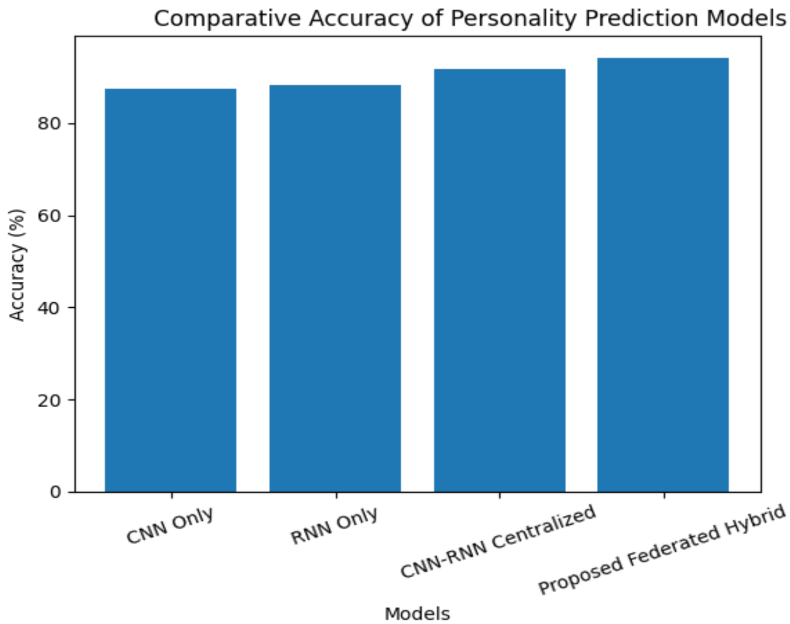

Figure 8: Comparative accuracy analysis of baseline and proposed personality prediction models

The accuracy performance of the various personality prediction models is compared in figure 8. As can be seen in the graph, both single CNN and RNN models are in the middle range of accuracy, which means that it is not adequate to rely on either spatial- or sequential-only features to model the intricate properties of handwriting. The combination of spatial and temporal feature learning can be seen to have an appreciable effect on the centralized CNNRNN model. Nevertheless, the suggested Attention-Enhanced Federated Hybrid model has the best accuracy of 94.2% proving the efficiency of the combination of CNN, BiLSTM, and attention mechanisms into a federated learning system. The graphical trend is a clear indication that hybrid modeling is an important tool in light of the increase in predictive ability, and federated learning does not undermine the performance at the expense of the data privacy. In general, the figure enhances the visual ability of proposing approach superiority, strength, and scalability.

Ablation Study

An ablation study was carried out to identify the contribution of main components in the proposed attention-enhanced federated hybrid CNN-BiLSTM model. The performance of four versions of the model (CNN only, CNN-BiLSTM no attention, CNN-BiLSTM with attention under centralized training, and fully featured CNN-BiLSTM-Attention with Federated Learning) were compared. An accuracy of 87.5% was obtained with CNN only, showing that spatial features of handwriting were not enough for predicting complicated personality traits. Including BiLSTM added an accuracy of 91.2%, while sequential patterns of handwriting dynamics contributed greatly to the personality identification. Accuracy increased to 93.5%, and precision improved as attention weights on the most significant writing sections improved. It could be seen that attention-based feature weighting minimizes false positives and enhances the understandability of the model. Accuracy increased to 94.2% while maintaining data privacy via decentralized training by adding Federated Learning. The small gap in performance with central and federated setups shows that privacy preserved learning could be performed without significant loss of predictive power. In short, each and every part is of great significance for the improvement of accuracy, model understandability, and privacy.

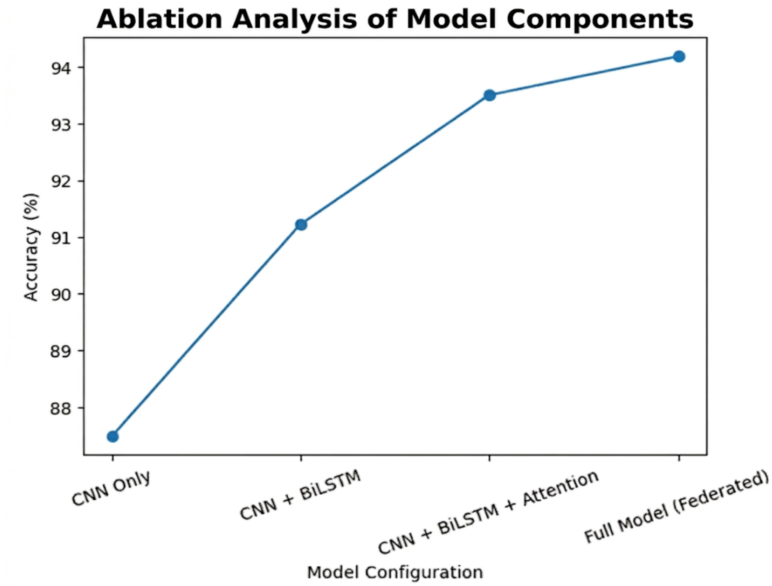

Figure 9: Ablation study for the proposed attention-enhanced federated hybrid model

The figure 9 shows the development of accuracy demonstrating the steady increase when each component BiLSTM, Attention mechanism, and Federated Learning is added to the original CNN model. The positive trend is an attestation of the fact that every module is positively correlated with the overall model performance, which proves the efficiency of the suggested hybrid federated architecture.

5 Discussion

The description of the experimental results indicates that the designed attention-enhanced hybrid federated CNN-BiLSTM model can be applied to personality prediction with handwritten documents, and its experimental results prove the model can effectively perform prediction and guarantee the privacy. The integration of spatial feature extraction (CNN), sequential modelling (RNN), attention mechanisms and federated learning contributes to the high-accuracy prediction. The hybrid CNN-BiLSTM model outperforms both CNN-only and RNN-only models in this task by modelling the structural handwriting characteristics and the writing dynamics (temporal order information of handwriting). The BiLSTM can effectively model the handwriting transition from stroke to stroke and the writing rhythm, implying that modelling both spatial information and sequential information is important for personality prediction. The performance of the model is further improved by using the attention mechanism because the model is guided to focus on the psychologically important handwriting region and learn more effective features. As confirmed by the ablation study, the model performance is significantly decreased after removal of the attention layer, and the attention mechanism indeed helps to capture discriminative writing information. Moreover, attention also accelerates the convergence speed of the model and leads to better generalisation across different writing styles. A key contribution of this work is the incorporation of federated learning to achieve privacy-preserving model training. Instead of uploading raw handwriting data to the server as in the traditional approach, proposed federated system can perform local training on clients and share only the model updates. The experimental results show that the proposed federated learning model obtains similar accuracy to centralised training with slight differences and fully guarantees the privacy of handwriting data. Also, stable convergence across communication rounds and consistent training dynamics indicate the robustness and scalability of the federated system for handwriting data across multiple clients. Overall, the proposed model has integrated predictive accuracy, interpretability, scalability and privacy protection for an automated handwriting personality prediction system.

6 Conclusion and Future Work

The experimental data prove the hypothesis that the proposed Attention-Enhanced Federated Hybrid CNN -BiLSTM model can be superior in terms of personality prediction with handwritten documents, achieving an Accuracy of 94.2% and a Precision of 92.8%. These distinct metrics validate that the model is both globally correct and specifically reliable in its positive trait predictions. As shown in the ablation study, every architectural element BiLSTM, attention mechanism, and federated learning is useful in improving performance in a progressive way. Attention layer refines the learning of discriminative features by giving priority to psychologically meaningful handwritings and federated learning grant the preservation of privacy without compromising the accuracy to a considerable degree. These results confirm that the suggested framework is a practical tradeoff between predictive accuracy, interpretability, robustness, and data privacy and, therefore, is a reliable and scalable solution to automated personality evaluation of sensitive handwritten data. This research can be expanded in a number of ways in the future. To begin with, the use of transformer-based architectures or vision transformers can also be used to increase feature representation capability. Second, prediction of multimodal personalities based on handwriting, voice, and behavioral data might enhance robustness in prediction. Third, higher-order federated optimization methods (including adaptive aggregation or secure multi-party computation) can be considered to enhance privacy assurances. Also, it can be explored on real-world deployment to edge devices and massive cross-institutional data to test scalability and real-time performance. Lastly, AI methods are explainable and can be combined to give more profound psychological explanations of the handwriting characteristics that are associated with dimensions of the personality.

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