Summer Internship cum Training Program - 2025

PROJECT REPORT

On

Personality Trait Classification Using Hybrid Deep Learning

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DECLARATION

I, Debesh Kumar Behera, Internship ID: CSINTERN/25/026, hereby declare that the report of the project entitled "Personality Trait Classification using Hybrid Deep Learning" which is being submitted to the Department of Computer Science and Engineering, in partial fulfillment of the requirements for the Summer Internship cum Training Program - 2025 (CSInternship-25) on "Deep Learning for Healthcare and Cryptography", is a bonafide report of the work carried out by me. The materials contained in this report have not been submitted to any University or Institution for the award of any degree. Any contribution made to this work by others, with whom I have worked at NIT Rourkela or elsewhere, is explicitly acknowledged in the dissertation. Works of other authors cited in this dissertation have been duly acknowledged under the sections "Reference" or "Bibliography".

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Title of Dissertation: Personality Trait Classification using Hybrid Deep Learning

The undersigned certify that they have read, and recommended for acceptance the project report entitled **Personality Trait Classification using Hybrid Deep Learning'** submitted by **Debesh Kumar Behera** in partial fulfillment of the requirements for the Summer Internship cum Training Program - 2025 (CSInternship-25) on "Deep Learning for Healthcare and Cryptography" in Department of Computer Science and Engineering.

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ABSTRACT

This project focuses on detecting personality traits from text using deep learning methods. By analyzing the words people write, it aims to predict their personality based on the Eight important personality traits: (Introversion-Extroversion, Intuition-Sensing, Thinking-Feeling, Judging-Perceiving). A hybrid deep learning model combining CNN and RNN layers was built to capture both important keywords and the overall context of the sentences. The model was trained on a dataset of social media posts labeled with personality scores and showed good performance in classifying traits. This work can help in areas like personalized recommendations, better human-computer interaction, and understanding user behavior through text.

Keywords:Personality Trait Classification, Hybrid Deep Learning, CNN, BiLSTM, GloVe Embedding, Fine-Tuning, Natural Language Processing (NLP), Text Classification, MBTI, Deep Learning, Sequence Modeling, Word Embeddings, Sentiment Analysis.

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1. LIST OF ABBREVIATIONS

ACF	Auto-correlation Function
AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
BiLSTM	Bidirectional Long Short-Term Memory
CNN	Convolutional Neural Network
DL	Deep Learning
DNN	Deep Neural Network
GPU	Graphics Processing Unit
MBTI	Myers–Briggs Type Indicator
ML	Machine Learning
NLP	Natural Language Processing
RNN	Recurrent Neural Network
ReLU	Rectified Linear Unit
SVM	Support Vector Machine
TF-IDF	Term Frequency–Inverse Document Frequency

2. INTRODUCTION

Personality plays a crucial role in understanding human behavior[1], preferences, and social interactions. With the rise of online communication and vast textual data, it has become possible to analyze personality traits using Natural Language Processing (NLP) and machine learning techniques[2]. This project focuses on detecting an individual's personality traits from their written text using deep learning, specifically hybrid models like BiLSTM and CNN. The approach offers a scalable and automated method for psychological profiling, with potential applications in hiring, mental health, personalized marketing, and more.

2.1. Background

The concept of personality trait classification is often based on psychological models like the MBTI (Myers–Briggs Type Indicator) or the Big Five Personality Traits. In this project, we use the MBTI framework

Introversion (I) vs. Extroversion (E)

Intuition (N) vs. Sensing (S)

Thinking (T) vs. Feeling (F)

Judging (J) vs. Perceiving (P)

Previous research has shown that linguistic patterns[1] can reveal these dimensions. With advancements in deep learning, models like CNNs (Convolutional Neural Networks) and BiLSTM (Bidirectional Long Short-Term Memory)[1] have proven effective in understanding complex sequences like text, making them ideal for this task.

2.2. Motivation

Understanding personality is important in fields like education, recruitment, and mental health. Traditional personality assessments are time-consuming, manual, and prone to bias. With the increasing use of digital communication, people leave behind valuable text data that reflects their personality. This project aims to use deep learning to automatically classify personality traits from text, making the process faster, scalable, and more accurate.

2.3. Objectives

1. To build a deep learning model using BiLSTM and CNN to classify personality traits from text.
2. To evaluate the model's performance using accuracy, precision, recall, and F1-score.

2.4. Problem statement

Traditional personality assessment methods are not scalable and can be biased or inefficient. There is a need for an automated solution that can accurately classify personality traits from user-generated text. This project proposes a hybrid BiLSTM-CNN deep learning model to address this challenge by learning meaningful patterns in textual data and classifying MBTI personality types effectively.

2.5. Scope of Project

This project focuses on classifying MBTI-based personality traits using a hybrid deep learning model combining BiLSTM and CNN. It involves:

1. Pre-processing and analyzing text data.
2. Building and training the hybrid model.

Evaluating model performance using standard metrics (accuracy, precision, recall, F1-score) The system is limited to English text and tested on publicly available MBTI datasets.

3. METHODOLOGY

The primary objective of this project is to classify personality traits from textual data using a hybrid deep learning approach. The methodology adopted involves multiple stages, including data preprocessing, embedding generation, model design, training, and evaluation. The overall workflow is described below.

3.1. Dataset Collection and Preprocessing

1. The dataset used for this project contains user-generated text labeled with personality traits based on the MBTI (Myers–Briggs Type Indicator) framework.
2. Each text entry was first cleaned to remove special characters, hyperlinks, emojis, and extra spaces.
3. Texts were then tokenized into sequences of words, and all words were converted to lowercase for consistency.
4. The sequences were padded to ensure uniform input length across all samples.

3.2. Word Embedding

To convert the textual data into numerical format suitable for deep learning models, two types of word embedding strategies were used:

1. Random Embedding: In the first model, word vectors were randomly initialized and learned during training.
2. GloVe Embedding: In the second and third models, pre-trained GloVe (Global Vectors for Word Representation) embeddings were used to provide semantically rich word representations[3].
3. With Fine-Tuning: Embeddings were updated during training.
4. Without Fine-Tuning: Embeddings remained static throughout training.

3.3. Training and Optimization

1. All models were trained using the categorical cross-entropy loss function and the Adam optimizer.
2. A validation set was used to monitor performance and avoid overfitting using early stopping.
3. Batch size and number of epochs were optimized experimentally.

3.4. Evaluation Metrics

The models were evaluated using:

1. Accuracy
2. Precision
3. Recall
4. F1-score

These metrics helped compare the models based on both overall and class-wise performance.

3.5. Tools and Frameworks Used

1. Programming Language: Python
2. Libraries: TensorFlow / Keras, NumPy, Pandas, Matplotlib
3. Embeddings: GloVe pre-trained vectors
4. Platform: Jupyter Notebook / Google Colab

4. MODEL ARCHITECTURE

4.1. Model 1: CNN + BiLSTM

This hybrid architecture combines Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) layers.

1. CNN layers are effective at capturing local features or n-gram patterns in the text (e.g., combinations of words or phrases), making them well-suited for understanding spatial or position-invariant features in word embeddings.

2. The output of the CNN is passed to a BiLSTM, which reads the sequence in both forward and backward directions to capture long-term dependencies and contextual relationships from both past and future tokens.

3. This combination leverages the feature extraction strength of CNNs and the context modeling ability of BiLSTM, making it ideal for sequence classification tasks like personality trait detection.

4.2. Model 2: CNN + BiLSTM (with GloVe Embedding without Fine-Tuning)

This model also uses GloVe embeddings, but here the embeddings are kept static:

1. The pre-trained GloVe vectors are not updated during training. This is often done to prevent overfitting when training data is limited, or to preserve the original semantic relationships in the embeddings.

2. While the CNN and BiLSTM layers still learn to classify based on input sequences, the word vectors remain fixed, relying only on the pre-learned semantic structure of GloVe.

3. This setup can lead to faster training and better generalization in some cases, though it may not capture dataset-specific nuances as well as the fine-tuned model.

4.3. Model 3: CNN + BiLSTM (with GloVe Embedding + Fine-Tuning)

This model extends the first by incorporating pre-trained GloVe (Global Vectors for Word Representation) embeddings:

1. GloVe provides semantic word embeddings trained on large text corpora (e.g., Wikipedia, Common Crawl). It helps the model start with a better understanding of word meanings.
2. These embeddings are fine-tuned during training, which means their weights are updated as the model learns. This allows the model to adapt the word vectors based on the personality trait classification task.
3. As a result, the model benefits from both general semantic knowledge (from pre-trained embeddings) and task-specific adjustments (from fine-tuning), improving its performance.

Table 4.1: Performance Comparison

Model	Average Overall Accuracy	Average Macro F1-Score	Average ROC AUC Score
CNN+BiLSTM	67.44%	0.43	0.56
CNN+BiLSTM (without fine-tuning GloVe embeddings)	78.01%	0.66	0.76
CNN+BiLSTM (with fine-tuned GloVe embeddings)	81.93%	0.72	0.84

Table 4.2: Performance Comparison

Model	Average Accuracy (%)	Average Macro F1-Score
Research Paper's Model (CNN+LSTM with GloVe)	93.37%	0.93
Your CNN+BiLSTM (with fine-tuned GloVe embeddings)	81.93%	0.72
Your CNN+BiLSTM (without fine-tuned GloVe embeddings)	78.01%	0.66

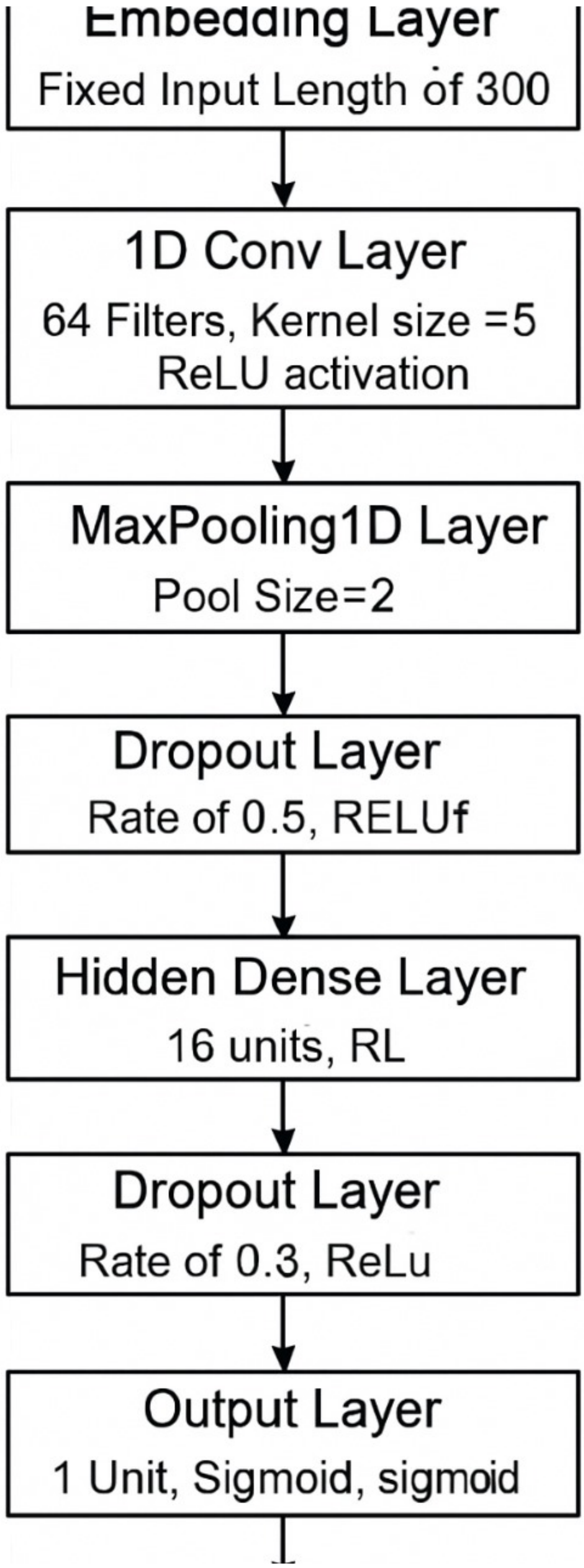

Figure 4.1: Model Training Snapshot

5. MODEL TRAINING

The hybrid deep learning models were trained using a combination of CNN and BiLSTM layers to classify personality traits from text. Input text was preprocessed, tokenized, and padded to a fixed length before being converted into vector form using either randomly initialized embeddings or pre-trained GloVe embeddings (with and without fine-tuning). The models were trained using the Adam optimizer and categorical cross-entropy loss, with accuracy, precision, recall, and F1-score as evaluation metrics. Early stopping and model checkpointing were used to prevent overfitting. While CNN captured local features, BiLSTM learned long-term dependencies, enabling effective personality trait classification.

6. MODEL EVALUATION

After training, the models were evaluated on a separate test set using various performance metrics to assess classification effectiveness and generalization.

6.1. Evaluation Metrics

1. Accuracy: Measures the overall correctness of the predictions.
2. Precision: Indicates the proportion of correctly predicted positive observations.
3. Recall: Measures how well the model identifies all relevant cases.
4. F1-Score: Harmonic mean of precision and recall, used especially when data is imbalanced.
5. Confusion Matrix: Provides class-wise insight into correct and incorrect predictions.

6.2. Confusion Matrix Analysis

The confusion matrix provided a detailed view of the model's predictions across different personality trait classes. It highlighted the number of correct predictions (true positives) and misclassifications (false positives and false negatives) for each class. This analysis helped identify which personality traits the model classified accurately and which were often confused with others. For example, if certain traits like "Thinking" and "Feeling" were frequently misclassified, it indicated overlapping language patterns in the text data. By analyzing these patterns, we could better understand the model's behavior and explore targeted improvements, such as data balancing or class-specific training enhancements.

	Predicted Sensing	Predicted Intuition
Actual Sensing	24	215
Actual Intuition	15	1481

Figure 6.1: Trait Classification

	Predicted Feeling	Predicted Thinking
Actual Feeling	826	113
Actual Thinking	167	629

Figure 6.2: Trait Classification

	Predicted Extrovert	Predicted Introvert
Actual Extrovert	~280	~120
Actual Introvert	~107	~1228

Figure 6.3: Trait Classification

	Predicted Perceiving	Predicted Judging
Actual Perceiving	891	157
Actual Judging	343	344

Figure 6.4: Trait Classification

7. CONCLUSION

In this project, a hybrid deep learning approach was proposed to classify personality traits from textual data using three different CNN + BiLSTM-based models. The first model used randomly initialized embeddings, while the second and third models used pre-trained GloVe embeddings—with and without fine-tuning, respectively. Experimental results showed that the model using GloVe embeddings with fine-tuning achieved the highest accuracy and overall performance, highlighting the benefit of combining semantic knowledge with task-specific training. The model without fine-tuning also performed well, indicating the effectiveness of pre-trained embeddings in capturing linguistic patterns. In comparison, the model with randomly initialized embeddings showed relatively lower performance due to the lack of prior semantic context. Overall, the study demonstrated that combining CNN and BiLSTM effectively captures both local and sequential features in text, and the use of fine-tuned word embeddings significantly enhances classification accuracy in personality trait prediction tasks.

8. FUTURE ENHANCEMENT

Although the proposed hybrid deep learning models achieved promising results in personality trait classification, there are several directions for future enhancement. The models can be trained on larger and more diverse datasets, including data from multiple social media platforms, to improve generalization. Incorporating additional linguistic features such as sentiment, emotion, or part-of-speech tagging could further enhance performance. Future work can also explore transformer-based architectures like BERT or RoBERTa for better contextual understanding. Moreover, integrating attention mechanisms into the existing CNN-BiLSTM framework may help the model focus on the most informative parts of the text. Finally, real-time personality prediction systems can be developed and deployed in applications such as personalized marketing, recommendation systems, or mental health analysis.

9. LIMITATIONS

- The model performance is constrained by the quality and size of the dataset used.
- It may not generalize well to other domains or informal text sources.
- Pre-trained embeddings like GloVe may miss out on domain-specific nuances.
- Computational resources limited the depth and complexity of the model architecture.
- The model does not consider multilingual or cross-lingual personality traits.

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