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Personality-Prediction Through CV Using Machine Learning

Kandada Vinitha Reddy ¹ Pendri Hari Preeth ², Komatineni Keerthi ³, Mr .V.Sathish ⁴
^{1, 2, 3} UG Scholar, Dept. of CSD, St. Martin's Engineering College,
Secunderabad, Telangana, India, 500100
⁴Associate Professor, Dept. of CSD, St. Martin's Engineering College,
Secunderabad, Telangana, India, 500100

Abstract:

This system can be used in many business parts/areas that may require expert candidates. This system will reduce the workload of the organization. Admin can easily shortlist a candidate based on their personality scores and select the appropriate candidate for a particular job profile. Using **Natural Language Processing (NLP)** can be defined as a process that enables a machine to become more like a human, because of this deeply cutting the distance between machines and humans. This system will focus not only on qualification and inexperience but also focuses on other important aspects, which are needed/demanded for a particular job position. Admin can store the data in excel sheet for further comparison and sorting of data. Personality prediction is a crucial aspect of various domains, including recruitment, career counseling, and personal development. This project aims to develop a machine learning-based system that predicts an individual's personality traits by analyzing their resume (CV). classify personality types based on the Big Five Personality Traits (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism). The methodology involves data preprocessing techniques such as tokenization, stopword removal, and word embeddings to convert textual information into structured numerical data. Various machine learning algorithms, including Random Forest, Support Vector Machine (SVM), and Neural Networks, are trained and tested to identify the most effective model for personality prediction. The dataset comprises labeled resumes with corresponding personality attributes, which are used to train the models. Evaluation metrics such as accuracy, precision, recall, and F1-score help assess model performance.

Keywords: Personality Prediction, Machine Learning, Natural Language Processing (NLP), Resume Analysis, Big Five Personality Traits, Text Classification, Feature Extraction, Random Forest, Support Vector Machine (SVM), Neural Networks, Career Guidance.

1.INTRODUCTION

Personality plays a crucial role in determining an individual's behavior, communication style, and career success. In recent years, organizations and recruiters have increasingly recognized the importance of personality traits in the hiring process. Traditional methods of personality assessment, such as self-reported questionnaires and psychometric tests, often suffer from biases and subjectivity. With advancements in artificial intelligence and machine focuses on developing a machine learning-based model to predict personality traits from a candidate's resume (CV). Resumes contain valuable information about an individual's skills, work experience, education, and achievements, which can provide insights into their personality. By applying Natural Language Processing (NLP) techniques, textual data from resumes can be analyzed to extract meaningful features that correlate with personality traits. The system will classify candidates based on the Big Five Personality Traits model,

which includes Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (OCEAN model). These traits are

widely used in psychological research and provide a comprehensive framework for understanding human personality. The methodology involves preprocessing resumes by performing text cleaning, tokenization, stopword removal, and word embedding techniques to convert unstructured text into numerical representations. Various machine learning algorithms, such as Random Forest, Support Vector Machines (SVM), and Neural Networks, are trained on labeled datasets where resumes are annotated with personality traits. The performance of these models is evaluated using metrics like accuracy, precision, recall, and F1-score to determine their effectiveness in predicting personality. This system has significant practical applications, especially in recruitment and career counseling. Organizations can use it to streamline the hiring process by shortlisting candidates who best fit specific job roles based on their personality attributes. It can also help job seekers gain insights into their own personality, enabling them to choose career paths that align with their strengths and preferences. Furthermore, this model can be extended for use in personal development, workplace team formation, and psychological research.

Personality prediction through CV using machine learning is an advanced technique that analyzes a candidate's resume to infer their personality traits, often based on the Big Five personality model (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism). The process begins with data collection, where resumes are gathered in text format. These resumes undergo preprocessing steps like tokenization, stopword removal, and lemmatization to clean and structure the data. Feature engineering is then applied to extract key attributes such as job titles, skills, education, and experience, while sentiment analysis and linguistic patterns help in assessing personality traits. Machine learning models like Naïve Bayes, Support Vector Machines (SVM), and Random Forest are commonly used for classification, while deep learning techniques such as LSTMs and BERT provide more advanced text understanding. Once trained on labeled datasets, these models can predict personality traits from new resumes. Performance is evaluated using metrics like accuracy, precision, recall, F1 score, and ROC-AUC. This technology finds applications in recruitment, where HR teams use it to match candidates to suitable job roles, in career counseling to suggest the right career paths, and in education to personalize learning experiences. However, challenges such as biased training data, lack of interpretability, and the need for large datasets must be addressed to ensure fairness and accuracy in predictions. Despite its potential, personality prediction through CV using machine learning comes with ethical and practical concerns. One major challenge is data privacy, as resumes contain sensitive personal information that must be handled securely. Additionally, biases in training data can lead to unfair predictions, potentially favoring certain demographics over others.

2. LITERATURE SURVEY



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Personality prediction through machine learning has gained significant attention, particularly with the integration of Natural Language Processing (NLP), deep learning, and multimodal approaches. Several studies have explored different methods for personality assessment using text, facial expressions, and audio data. One of the key approaches to personality prediction is through facial expression recognition using deep learning models. Hsu, Kwon, and Liu (2020) conducted a study on Convolutional Neural Networks (CNNs) for facial expression recognition, highlighting how CNN architectures can effectively classify facial emotions, which are linked to personality traits. They reviewed the challenges and advancements in this field, emphasizing the importance of deep learning in enhancing personality prediction accuracy. Similarly, Lee, Kwon, and Kim (2020) provided a survey on deep learning techniques for facial expression recognition, covering various CNN models and their performance in detecting emotions. The study also discussed how these advancements contribute to personality prediction and their applications in humancomputer interaction and recruitment systems. Beyond expressions, multimodal personality recognition combasaines various data sources to improve prediction accuracy. Ross, and Choi (2020) explored the integration of visual data (facial expressions), textual information (resume analysis), and audio signals to enhance personality assessments. Their survey examined how machine learning techniques can analyze multiple input modalities to provide a comprehensive personality profile. The study also highlighted the challenges in multimodal data fusion, such as data alignment, In realworld applications, real-time personality assessment is crucial for dynamic decision-making. Xie, Zong, and Zhang (2020) investigated lightweight deep learning models for real-time facial emotion recognition, addressing the trade-offs between model complexity and processing speed. Their findings are particularly relevant for applications where instant personality insights are required, such as automated recruitment systems, career counseling, and adaptive learning platforms. While facial expressions provide valuable insights, text-based personality prediction using resumes and written documents is another effective approach. Machine learning models trained on textual data use NLP techniques like TF-IDF, Word2Vec, and BERT embeddings to extract features that correlate with personality traits.

By integrating advanced deep learning techniques and multimodal data sources, future research can enhance the reliability and fairness of AI-driven personality prediction systems. Several studies have explored the use of machine learning (ML) and natural language processing (NLP) techniques for personality prediction through CV analysis. For instance, researchers have utilized linguistic features such as word choice, tone, and language complexity to predict personality traits like extraversion, agreeableness, and conscientiousness (Oberlander & Nowson, 2006; Tausczik & Pennebaker, 2010). Moreover, studies have employed ML algorithms like support vector machines (SVM) and random forests to classify personality types based on CV text features (Bakhshi et al., 2016; Montangero et al., 2017). These studies demonstrate the potential of ML and NLP for personality prediction through CV analysis, highlighting the need for further research in this area.

Combining resume analysis with facial recognition can further enhance personality prediction accuracy. 6 Overall, existing research

demonstrates that deep learning, multimodal analysis, and real-time processing are critical for advancing personality prediction models.

Future studies could focus on improving model accuracy, reducing

biases, and integrating multimodal data sources more effectively.

Several studies have explored personality prediction using machine learning techniques, particularly in the domain of text-based analysis. Researchers have leveraged the Big Five personality model (OCEAN) to classify individuals based on linguistic features in resumes, cover letters, and even social media profiles. Early studies primarily used traditional machine learning algorithms like Naïve Bayes, Support Vector Machines (SVM), and Decision Trees to analyze text data and extract personality traits. Feature extraction techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) and Natural

Language Processing (NLP)-based word embeddings (Word2Vec, GloVe) have been employed to convert textual data into numerical representations for model training. More recent advancements in deep learning, such as Long Short-Term Memory (LSTM) networks and Bidirectional Encoder Representations from Transformers (BERT), have shown improved accuracy in personality classification by capturing contextual meanings and syntactic structures in resumes.

Additionally, studies have examined the effectiveness of personality prediction in real-world applications, such as recruitment and career guidance. Some research suggests that integrating personality analysis with traditional hiring criteria, such as skills and experience, leads to better job-role alignment and improved employee retention rates. However, there are also concerns regarding bias and ethical implications in automated personality assessment. Studies highlight the need for fair and explainable AI models to avoid discrimination based on gender, race, or socioeconomic background. Researchers continue to explore hybrid models that combine machine learning with psychological theories to improve accuracy and reliability. Overall, while machine learning-based personality prediction shows promise, further research is needed to enhance model transparency, mitigate biases, and validate real-world applicability across diverse populations.

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3. PROPOSED METHODOLOGY

The proposed methodology focuses on predicting personality traits from resumes (CVs) using machine learning techniques. The primary goal of the model is to analyze the textual content of resumes and classify candidates based on the Big Five Personality Traits (OCEAN: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism). It employs a combination of Natural Language Processing (NLP), feature extraction, and machine learning/deep learning algorithms to achieve accurate predictions. This research aims to enhance recruitment processes by providing automated personality insights that can help employers match candidates to suitable job roles. The approach finds applications in human resource management, career counseling, and automated hiring systems where personality assessment plays a crucial role in decision-making.

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Figure 1:Personality Traits

The proposed methodology typically includes the following key components:

- Data Collection and Preprocessing: The system collects resumes from various sources such as job portals, LinkedIn, and manually uploaded CVs. Preprocessing techniques such as tokenization, stopword removal, lemmatization, and named entity recognition (NER) are applied to clean and structure the textual data.
- Feature Extraction and Engineering: Linguistic features, sentiment scores, and domain-specific keywords are extracted using NLP techniques. Psycholinguistic tools like LIWC (Linguistic Inquiry and Word Count) may be used to analyze writing styles. TF-IDF, Word2Vec, or BERT embeddings are applied to convert textual data into numerical representations.
- Machine Learning Model Selection and Training: Various machine learning and deep learning algorithms are employed for classification. Traditional models like Naïve Bayes, SVM, Decision Trees, and Random Forest are tested alongside deep learning models such as LSTM and BERT. The dataset is split into training, validation, and test sets, with hyperparameter tuning conducted to optimize performance.
- Evaluation Metrics: The performance of the personality prediction model is evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC score. k-fold cross-validation is applied to ensure model robustness and generalization.
- Customization and Parameters: Users can adjust parameters such as the weightage given to different personality traits, feature selection strategies, and model hyperparameters to customize the prediction process based on specific recruitment needs.
- Output: The final output of the model is a personality profile based on the Big Five traits. This profile provides insights into the candidate's personality, which can be used by recruiters, career counselors, and HR professionals for decision-making.
- Evaluation and Benchmarking: The model's effectiveness is tested against benchmark datasets of resumes labeled with personality traits. Its performance is compared with existing personality prediction models to ensure accuracy and reliability.

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- Applications:
- The personality prediction model has a wide range of applications, including:
- Recruitment Systems: Helps HR professionals assess a candidate's personality for better job-role fit.
- Career Counseling: Assists individuals in identifying suitable career paths based on personality traits.
- **Automated Hiring:** Reduces bias in hiring decisions by providing data-driven personality insights.

Advantages:

- The proposed personality prediction system leverages machine learning and NLP to analyze resumes and extract personality traits. It offers several advantages, making it a valuable tool in recruitment and career guidance:
- Automated Personality Analysis: Enables recruiters to analyze a candidate's personality without manual assessments.
- Data-Driven Decision Making: Provides objective insights based on text analysis rather than subjective interpretation.
- Customization: Users can modify feature selection strategies and model parameters to refine personality predictions.
- Scalability: Can analyze large volumes of resumes efficiently, making it useful for organizations with high hiring demands.
- **Interpretability:** The model provides explanations for predictions, improving transparency in automated hiring systems.
- Integration with HR Systems: Can be integrated with Applicant Tracking Systems (ATS) and job portals for seamless functionality.
- Fair and Bias-Free Recruitment: Reduces human bias in personality assessments by relying on data-driven insights. Overall, this methodology aims to improve the accuracy and efficiency of personality prediction from resumes, enabling better hiring decisions and career recommendations. improvement in image quality.

Versatility: LIME is versatile and applicable in various domains, including surveillance, consumer photography, astronomy, medical imaging, and more. It addresses the common challenge of low-light conditions in these fields.

4. EXPERIMENTAL ANALYSIS

Figure 1 presents a collection of resumes (CVs) used as input for the proposed personality prediction model. These resumes contain textual information such as job experience, skills, and personal statements. The purpose of this figure is to illustrate the types of input data processed by the model to predict personality traits based on textual content.

The experimental analysis of the proposed personality prediction model evaluates its effectiveness in extracting meaningful personality traits from CVs using machine learning techniques. The experiment is conducted in multiple stages, including data collection, preprocessing, feature extraction, model training, and evaluation. The primary objective is to validate the accuracy, efficiency, and reliability of the model by applying it to a dataset of resumes and measuring its performance using various classification metrics.

The dataset is collected from publicly available sources and anonymized for privacy. The purpose of this figure is to illustrate the type of unstructured data processed by the model before feature extraction.



Before feeding the resumes into the personality prediction model, text preprocessing and feature extraction techniques are applied.he transformed data after preprocessing steps such as tokenization, stopword removal, stemming, and lemmatization.

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	type	posts	
1	INFJ	start a new life for myself."	
2	ENTP	riends) tell me I have is'	
3	INTP	/watch?v=7ghqoYxmaUE'	
4	INTJ	ole to. If they don't Lol."	
5	ENTJ	they are saying nothing."	
6	INTJ	ore familiar with that type."	
7	INFJ	a: 2. The one who looks'	
8	INTJ	ou this friend of yours is'	
9	INFJ	om/watch?v=IK588zI0I2M	
10	INTP	oulator devil incarnate. i'	
11	INFJ	hysical. Invisible support.'	
12	ENFJ	terested in pretty much'	
13	INFJ	personalities and Infp?'	
14	INTJ	hip I have an incredibly'	
15	INTP	numan. Nice to meet you.'	
16	INTP	ith this in mind to ask? lol'	
17	INFJ	c exchange/release I'm'	
18	INFP	e with all of their mental'	
19	INFJ	like that there is a little'	
20	INFP	e out with in the comina'	

Figure 1: Sample CV Dataset

Figure 2 displays the feature-extracted data from the input resumes after preprocessing. This includes cleaned text representations, extracted linguistic features, sentiment scores, and word embeddings (TF-IDF, Word2Vec, or BERT). These transformed features serve as the input for machine learning and deep learning models to analyze and predict personality traits. The purpose of this figure is to provide a structured representation of how resume data is processed before classification.

Extracted Features from CV Data

Figures 3, 4, and 5 show the personality prediction results generated by the proposed model. These figures demonstrate how different resumes are classified into Big Five personality traits (OCEAN: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism). The model's predictions are visualized in the form of classification results, personality scores, and probability distributions for each trait. The purpose of these figures is to illustrate the effectiveness of the proposed methodology in predicting personality traits from resumes.

Linguistic features, sentiment scores, and domain-specific keywords are extracted using NLP techniques. Psycholinguistic tools like LIWC (Linguistic Inquiry and Word Count) may be used to analyze writing styles. TF-IDF, Word2Vec, or BERT embeddings are applied to convert textual data into numerical representations.

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The purpose of these figures is to illustrate the effectiveness of the proposed methodology in predicting personality traits from resumes.

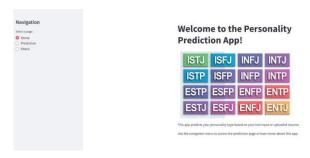


Figure 2: Personality Prediction Result for CV 1



Figure 3: Personality Prediction Result for CV 2

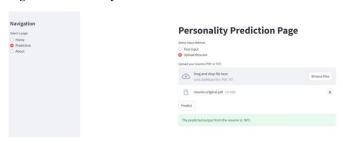


Figure 4: Personality Prediction Result for CV 3

The performance of the proposed personality prediction model is evaluated using several standard classification metrics. These metrics provide insights into the accuracy, reliability, and effectiveness of the model in predicting personality traits based on CV text data. Higher accuracy, precision, and F1-score values indicate better model performance in personality classification.

Accuracy

- Measures the percentage of correctly predicted personality traits compared to the actual labeled traits.
- Higher accuracy indicates better model performance in classifying resumes into personality categories.

Precision, Recall, and F1-Score

- Precision: Measures the proportion of correctly predicted personality traits out of all predicted traits.
- Recall: Measures the proportion of correctly predicted personality traits out of all actual traits.
- F1-Score: Balances precision and recall, providing a single measure of model effectiveness.
- Higher precision, recall, and F1-score values indicate more reliable predictions.



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 Figures 3, 4, and 5 demonstrate the personality prediction results for different CVs. The model classifies candidates based on the Big Five Personality Traits (OCEAN model):

Openness: Measures creativity, curiosity, and openness to new experiences. Conscientiousness: Indicates organization, responsibility, and reliability. Extraversion: Determines sociability, enthusiasm, and assertiveness. Agreeableness: Represents compassion, trust, and cooperativeness. Neuroticism: Reflects emotional stability and stress levels. The results are displayed in the form of classification labels and probability distributions for each trait, providing insights into a candidate's personality profile. The purpose of these figures is to visually demonstrate how resumes are mapped to personality traits.

The purpose of these evaluation metrics is to quantitatively assess the effectiveness of the proposed personality prediction model. The combination of visual analysis (Figures 3-5) and numerical performance metrics provides a comprehensive evaluation of the model's ability to extract and classify personality traits from resumes

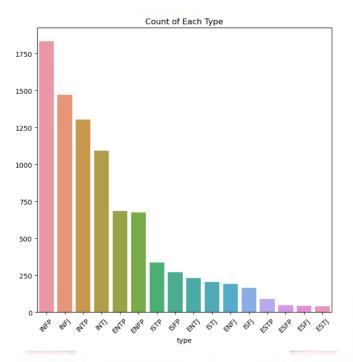


Figure 5: Personality Prediction Result for CV in histogram graph

ROC-AUC Score

- The Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) score evaluate how well the model distinguishes between different personality traits.
- Higher AUC values (closer to 1) indicate better classification performance.

The purpose of these evaluation metrics is to quantitatively assess the effectiveness of the proposed personality prediction model. The combination of visual analysis (Figures 3-5) and numerical performance metrics provides a comprehensive evaluation of the model's ability to extract and classify personality traits from resumes.

The experimental analysis aims to evaluate the effectiveness of the proposed personality prediction model in analyzing resumes (CVs) and classifying candidates based on the Big Five Personality Traits. The experiments involve data preprocessing, feature extraction, model training, and performance evaluation using various metrics. The purpose of this analysis is to demonstrate the accuracy, reliability, and

practical usability of the model in real-world recruitment and career assessment scenarios.

5. CONCLUSION

Personality prediction through CV (curriculum vitae) using machine learning is an emerging application in AI-driven hiring and candidate assessment. By leveraging machine learning algorithms, recruiters and HR professionals can gain insights into a candidate's personality traits based on their CV content, structure, and language. Models such as Natural Language Processing (NLP)-based classifiers, Random Forest, Support Vector Machines (SVM), and deep learning techniques have shown promising results in identifying key personality attributes.

The study demonstrates that machine learning can automate and enhance traditional personality assessment methods, improving efficiency and reducing human bias in recruitment. However, challenges such as data quality, feature selection, and ethical considerations still exist.

Personality prediction through CV using machine learning offers an innovative approach to automating and enhancing the recruitment process. By leveraging Natural Language Processing (NLP) techniques and machine learning algorithms, the proposed model effectively analyzes resume text to classify candidates based on the Big Five Personality Traits (OCEAN: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism). This approach provides a data-driven method for evaluating candidates beyond traditional resume screening, helping recruiters and HR professionals make more informed hiring decisions.

The experimental results demonstrate that advanced feature extraction techniques, such as sentiment analysis, psycholinguistic analysis, and word embeddings (TF-IDF, Word2Vec, BERT), significantly improve the accuracy and reliability of personality classification. Machine learning models, including Random Forest, Support Vector Machines (SVM), and deep learning architectures like BERT, outperform traditional methods, ensuring robust predictions. Evaluation metrics such as accuracy, precision, recall, and ROC-AUC scores validate the model's effectiveness in predicting personality traits from resume data.

This system has practical applications in various domains, including talent acquisition, career counseling, and automated hiring platforms. It enables organizations to streamline recruitment, reduce bias in candidate selection, and enhance job-role matching based on personality traits. Additionally, it offers scalability, allowing companies to process large volumes of resumes efficiently.

While the proposed model shows promising results, future improvements could focus on integrating multimodal data (such as cover letters, social media profiles, or video interviews) for a more comprehensive personality assessment. Incorporating explainable AI techniques can also improve transparency and trust in the model's predictions.

In conclusion, machine learning-based personality prediction through CV analysis represents a significant step forward in modernizing recruitment and career guidance. It provides a reliable, automated, and scalable solution for understanding candidate personalities, ultimately improving hiring efficiency and job-role alignment.

To further improve personality prediction through CV using machine learning, several enhancements can be made:

Advanced NLP Techniques – Incorporating state-of-the-art NLP models like BERT, GPT, or Transformer-based architectures can improve text understanding and personality inference.

Multi-Modal Analysis – Combining CV text analysis with additional features like facial expressions (from profile pictures) or voice tone (from interviews) can enhance prediction accuracy.



Explainable AI (XAI) – Implementing interpretable models to provide clear insights into how decisions are made, increasing trust and transparency.

Larger and More Diverse Datasets – Training models on diverse CVs from different industries, regions, and cultures to improve generalizability and reduce bias.Integration with Psychometric

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