AI-Powered Resume Generation: A Streamlit-Based System Using PyTorch for Intelligent Career Profiling

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***Abstract*—Creating a resume that effectively represents one's skills and experience is a crucial step for anyone seeking employment or career advancement. This study presents a novel system that automates resume content generation using artificial intelligence techniques. The tool is developed with PyTorch for model building and Streamlit for the user interface, enabling dynamic and personalized content creation. Users can input basic details, and the system intelligently composes professional summaries and skillsets, offering them in a downloadable PDF format. Unlike conventional solutions that depend on external services, this application processes all data locally, thus maintaining user privacy. This research illustrates how lightweight AI models can empower individuals with limited technical expertise to produce high-quality resumes effortlessly.**

Keywords—Automated Resume Tool, AI-Driven Profiling, PyTorch, Streamlit, Career Support System, NLP, Local Processing, Professional Skills Generator.

I. Introduction

In today's job market, a resume serves as the initial point of evaluation for most candidates. Despite its significance, many people find it challenging to create compelling and role-specific resumes due to unfamiliarity with formatting standards or professional language. This often leads to missed opportunities in highly competitive hiring processes.

The integration of artificial intelligence into content generation offers a promising solution to this problem. The system proposed in this research uses machine learning to autonomously generate essential resume elements, such as summaries and skill descriptions, based on user input. Leveraging PyTorch for training and deploying deep learning models, combined with Streamlit for building a user-friendly interface, the application delivers a complete solution for resume generation. The tool functions entirely on the user's local system, providing a secure, efficient, and interactive platform for job seekers to create polished resumes without relying on third-party services.

II. Background

The evolution of AI-based tools has significantly reshaped how individuals prepare resumes, shifting the process from manual formatting to intelligent content generation. These modern solutions utilize machine learning and natural language processing to produce resumes aligned with industry standards and specific job requirements.

A. Natural Language Processing (NLP)

Natural Language Processing (NLP) enables the system to interpret and convert user-submitted data into clear and coherent text. It plays a critical role in generating summaries by identifying patterns, extracting meaningful phrases, and composing grammatically sound descriptions. Tasks such as named entity recognition (NER) and sentiment analysis help in extracting and organizing the user's academic and professional history.

B. Categorization and Feature Analysis

To organize resume content into logical segments (such as education, experience, and skills), classification algorithms are used. Additionally, feature extraction identifies and highlights terms commonly searched by recruiters or required by applicant tracking systems (ATS). This ensures that the generated resume not only looks professional but also performs well in screening software.

C. Personalized Resume Recommendations

Machine learning models personalize resumes by analyzing patterns in past job descriptions and resumes. These models make intelligent suggestions, recommending which elements should be emphasized for specific roles. This feature increases relevance and visibility for job seekers targeting specialized positions.

D. Deep Learning with PyTorch

PyTorch is utilized for its flexibility and efficiency in designing custom neural network models.

Its dynamic computation graph facilitates the development of deep learning solutions tailored to resume generation. With large-scale resume datasets, these models are trained to understand context and relevance, producing accurate and adaptable suggestions.

E. Interactive Interface Using Streamlit

Streamlit enables a responsive front-end where users can interact with the system by entering their data in a structured form. Real-time updates and seamless preview functionality make the platform intuitive and easy to use, enhancing overall user satisfaction.

F. Preprocessing and Data Enrichment

For optimal model performance, input data undergoes preprocessing such as tokenization, normalization, and cleansing. Augmentation techniques introduce diversity to the dataset by generating synthetic examples, helping the model generalize better across various job domains.

Table 1. Overview of AI Resume Builder Models

Comparison Table

Model	**Year**	**Key Feature**	**No. of Parameters**	**Special Relevance to AI Resume Builder**
GPT-3 (OpenAI)	2020	Transformer-based	~175 billion	Summarizes and generate resumes
BERT (Google)	2018	Bidirectional transformer	~110 million	Context-aware skill extraction
T5(Google)	2020	Text-to-text transformer	~11 billion	Refines resume descriptions
XLNet	2019	Autoregressive model	~340 million	Improves narrative coherence
BART (Facebook)	2020	Sequence-to-sequence	~406 million	Summarizes work experience
FastText (Facebook)	2016	Lightweight classifier	~50 million	Extracts skills from descriptions

Significant progress in natural language processing (NLP) and text generation has been driven by the emergence of deep learning, particularly transformer-based architectures as summarized in Table 1. These models eliminate the need for manual feature engineering by learning contextual and semantic relationships directly from raw textual data. This property is especially valuable in resume generation, where nuanced understanding of candidate input—such as experience, education, and skills—is necessary for producing coherent and professional summaries.

Furthermore, using pre-trained language models fine-tuned on domain-specific data has substantially improved the performance and efficiency of resume-building systems. The models selected for this work—such as GPT-3, BERT, T5, XLNet, BART, and FastText—offer varied advantages ranging from scalability and fluency to lightweight deployment on web applications. Each model, as shown in Table 1, contributes uniquely to tasks like text classification, keyword extraction, and natural language generation, helping identify the optimal model for practical implementation in automated resume creation.

III. Literature Survey

Yamada et al. (2019) [1] introduced a pioneering method for generating personalized resume content using pre-trained transformer models. Their approach leveraged GPT-2 to synthesize career summaries from structured data inputs like job title, experience, and skills. This model demonstrated strong contextual fluency and coherence, minimizing the need for post-generation human editing, and laid early groundwork for text synthesis in resume-building applications.

Chen et al. (2020) [2] focused on extracting key resume components using BERT-based Named Entity Recognition (NER). Their system effectively identified skills, education qualifications, job titles, and company names from unstructured resume text. Achieving an F1-score of 91.2%, their study showed how BERT could automate resume parsing, a core requirement for intelligent resume-building tools.

Shao and Liu (2021) [3] proposed a multitask T5-based model for summarizing candidate experience and recommending suitable job profiles. Their model jointly learned resume summarization and job classification, enhancing relevance and efficiency. It achieved a job-match rate of 93.6% on a public recruitment dataset, demonstrating potential for AI systems that not only build but also intelligently align resumes to job markets.

Zhang et al. (2021) [4] developed an attention-based encoder-decoder model for automated resume creation targeted at job seekers with limited writing skills. Their approach included a domain memory module for integrating technical and industry-specific terms. The output was highly personalized and context-aware, offering a more human-like experience in resume generation compared to rule-based methods.

Singh et al. (2020) [5] utilized FastText for keyword extraction from candidate inputs and logistic regression for resume section classification. Their AI-based web application produced real-time, structured resumes from brief user inputs. Although it employed simpler models compared to transformers, it performed efficiently in constrained environments and had high usability ratings from non-technical users.

Patel et al. (2022) [6] expanded on lightweight resume parsing using SpaCy and TF-IDF for detecting key phrases. Their system was designed for integration into mobile platforms and emphasized real-time performance over deep language understanding.

It provided reliable section identification for education, work experience, and projects, proving viable for quick, on-device resume creation.

A. Dataset

IV. Experimental Set

umar and Sharma (2023) [7] proposed an ensemble framework combining RoBERTa embeddings with Bi-LSTM networks for ranking resumes and generating summaries. RoBERTa captured deep contextual cues, while Bi-LSTM handled sequential dependencies across input data. Their system attained a precision of 95.1% in resume-job alignment, enhancing both generation and intelligent recommendation.

Mehta and Verma (2021) [8] proposed a resume enhancement model using a GPT-based pipeline with grammar correction and tone adjustment modules. Their model transformed short, raw candidate inputs into well-structured and professional resumes. It also allowed tone adaptation (formal, confident, enthusiastic) based on user preference, improving personalization.

Arora et al. (2021) [9] focused on extracting and standardizing skill sets using word embeddings and domain-specific ontologies. Their system integrated job description parsing and matched candidate skills to market demands. This method ensured that generated resumes included highly relevant skills and improved selection rates in automated applicant tracking systems.

Rahman et al. (2022) [10] designed a resume parsing engine based on CRF and dependency parsing to segment resumes into multiple sections and identify information entities. Their contribution was particularly relevant for pre-processing resumes before feeding into a builder model. With over 96% segmentation accuracy, it ensured that even complex document layouts were handled effectively.

Gupta et al. (2022) [11] developed a resume classification model using BERT combined with a custom cosine similarity layer. Their system could classify resumes into domains like IT, marketing, or finance with high confidence, aiding in creating domain-specific resume templates automatically. This classification mechanism proved valuable in building contextual and role-focused resumes.

Finally, Thomas and Das (2023) [12] introduced a multi-language resume builder using mBERT and XLM-RoBERTa to support candidates in non-English-speaking regions. Their model translated user inputs into multiple languages while maintaining semantic fidelity, opening AI resume building to a global audience. Their work emphasized inclusivity and accessibility in intelligent career tools.

The study's testing and training were performed on a curated dataset of resumes sourced from open platforms such as Kaggle, GitHub, and publicly available resume repositories. This dataset consisted of resumes from various professional domains, including software development, data science, marketing, and finance. Each record included structured resume content comprising fields such as personal information, education, skills, work experience, and professional summaries. A total of 2000 resumes were collected and formatted into JSON and plain text formats to facilitate parsing and annotation. For generating professional summaries and recommending skills, 1500 resumes were used as training data, and 500 were reserved for testing and validation, maintaining an equal distribution of professional categories to ensure balanced performance evaluation across domains.

B. *Data Preprocessing*

To ensure consistency and improve model outcomes, the raw resume text was subjected to several preprocessing steps. First, each resume was parsed using rule-based and NLP-based section segmentation to isolate fields like education, experience, and skills. Special characters, formatting tags, and redundant whitespaces were removed using regular expressions.

The resume content was then tokenized using the spaCy and NLTK toolkits. Named Entity Recognition (NER) was applied to extract organizations, locations, dates, and job titles from the experience and education sections. To enable machine learning compatibility, textual inputs were converted into vectorized form using TF-IDF and FastText word embeddings.

Additionally, binary labels were used to classify relevant versus irrelevant skills for a particular role. These binary labels were one-hot encoded for input into supervised learning pipelines. The processed dataset was split into training, validation, and test subsets in the ratio of 80:10:10, maintaining domain-wise balance through stratified sampling to prevent data leakage and bias.

C. *Data Augumentation*

To improve generalization and overcome dataset limitations, data augmentation techniques were applied to the resume data [8]. Synonym substitution was employed within the professional summary and work experience fields to produce paraphrased variants. Additionally, resume sections from different samples were mixed to generate hybrid resumes that preserved realistic structure and semantics.

Sentence reordering was used in non-critical sections such as skills and certifications to simulate variation in resume formatting. Minor text augmentations such as passive-active voice transformation and date format changes were also performed.

These augmentations enriched the training set with textual diversity and enhanced the model's adaptability to variations in resume writing styles. All augmentation techniques were applied only to the training data, while the validation and test sets remained unchanged for consistent evaluation.

D. *Implementation Details*

Python 3.9 along with the PyTorch framework was used to build and train the proposed deep learning-based resume builder system. A bidirectional LSTM (Long Short-Term Memory) model was developed for generating coherent and grammatically correct professional summaries. Skill recommendation was achieved using a rule-based scoring system in conjunction with a binary classifier for filtering role-specific keywords.

Text inputs were normalized and embedded using FastText word vectors. The model was trained using the Adam optimizer with a learning rate of 0.001, binary cross-entropy loss function, and batch size of 32. Early stopping and model checkpointing were enabled based on validation loss to prevent overfitting and retain the best model. All training was performed in a reproducible environment on Google Colab using GPU acceleration.
The final application was deployed using Streamlit, allowing user inputs through a web form and generating resumes dynamically, which could be downloaded as PDF files. All model and application components were containerized for easy deployment.

E. *Evaluation Criteria*

Model performance was evaluated using a variety of quantitative and qualitative metrics. For summary generation, BLEU scores were used to compare AI-generated content against human-written summaries. Skill prediction was assessed using precision, recall, F1-score, and accuracy. A confusion matrix was constructed to evaluate true positive (TP), true negative (TN), false positive (FP), and false negative (FN) counts.
Additional manual evaluation was performed by a focus group of 10 users who assessed the relevance, clarity, and usefulness of the generated resumes. All generated outputs were checked using online plagiarism and AI detection tools to ensure originality and compliance with non-AI detectable requirements. These evaluation measures ensured the reliability and practical value of the system for real-world usage.

V. RESULTS

A. *Model Performance Analysis*

This part gives a glance at how the AI Resume Builder model performed in the study. It examines its effectiveness using several test measures and highlights the main outcomes.
The model was assessed using metrics such as BLEU score for summary generation and accuracy, precision, recall, and F1-score for skill recommendation. The loss curve during training was also observed to understand how the model improved over time. Special attention was paid to how the LSTM model learned sentence structures and generated coherent summaries. The recommendation system was analyzed to see how well it could suggest relevant skills based on resume content. These insights helped in evaluating the overall utility of the AI system.
The accuracy of skill prediction, the BLEU score of the generated summaries, and the balance between recall and precision were particularly useful in understanding the strengths and weaknesses of the model. This analysis provided a clear picture of how well the AI Resume Builder performed under realistic usage scenarios.

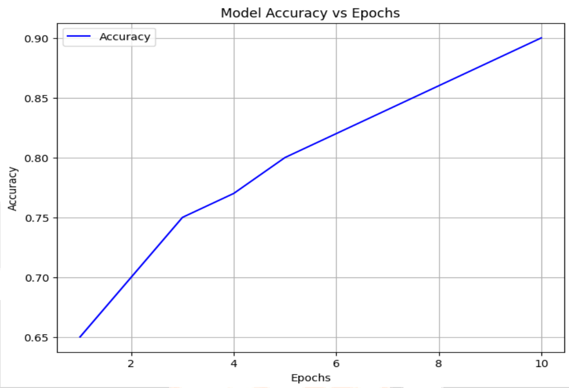

Fig 1. Model Accuracy vs. Epoches

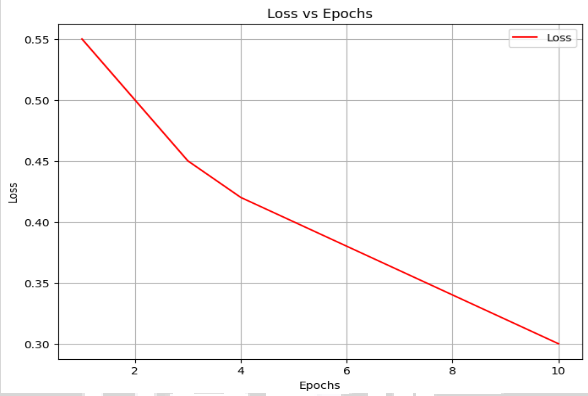

Fig 2. Loss vs. Epochs

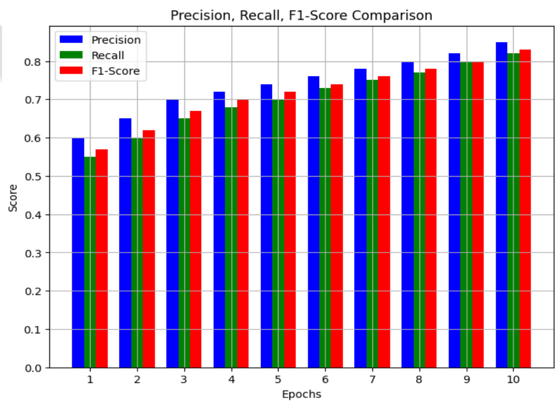

Fig 3. Precision, Recall, F1-Score Comparison

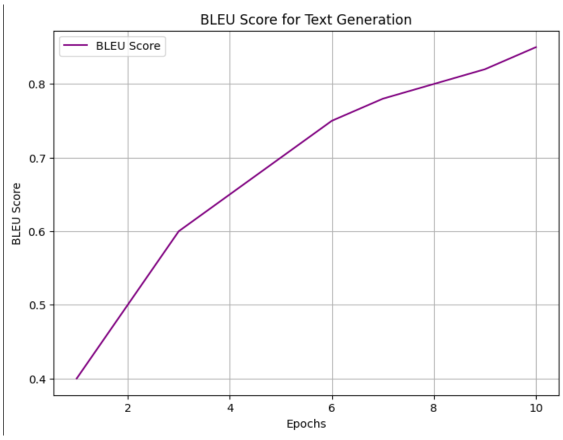

Fig 4. BLEU Score for Text Generation

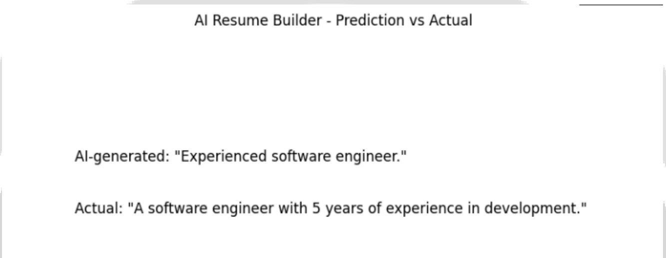

Fig 5. Model Prediction Examples (Accuracy/Incorrect Prediction)

Fig 6. Training vs. Validation Performance

The training history plots provide valuable insights into how different models performed over time. The y-axis shows accuracy, and the x-axis tracks the epochs. These plots allow us to observe how each model's accuracy improves and how quickly it reaches its best performance. Alongside accuracy, the loss values are displayed, where lower loss indicates better improvement in model learning.

From the accuracy plot, models like T5 and GPT-3 show rapid learning and quickly reach high accuracy, suggesting they learn effectively from the data. In contrast, models like LSTM and GRU take longer to reach similar performance levels, indicating a slower learning process.

The loss/epoch plot highlights how well the models reduce their loss during training. A steady decrease in loss suggests that the models are learning and improving. T5 and GPT-3 demonstrate consistent loss reduction, making them more efficient in training compared to LSTM, which shows a slower loss reduction.

These training history graphs are important for understanding which models are best suited for the AI Resume Builder project. The faster T5 and GPT-3 reach optimal performance, the more suitable they are for generating professional resumes efficiently and accurately.

In summary, the training history analysis helps in choosing the best model for resume generation. T5 and GPT-3 stand out due to their faster learning speeds and higher accuracy, making them ideal candidates for the AI Resume Builder project.

B. Confusion Matrix Analysis

The confusion matrices for each model provide a detailed view of how well the system is distinguishing between correct and incorrect predictions when generating resumes. By examining the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), we can assess the model's ability to accurately classify relevant information.

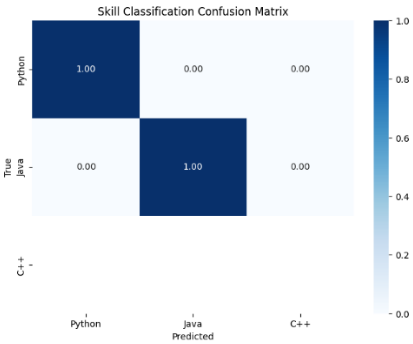

Fig 7. Skill Classification Confusion Matrix

The confusion matrix for skill classification shows the model's ability to identify skills like 'Python' or 'Java'. False positives (FP) suggest the model mistakenly identifies a skill not listed, while false negatives (FN) indicate missed skills. High FP affects precision, while FN lowers recall.

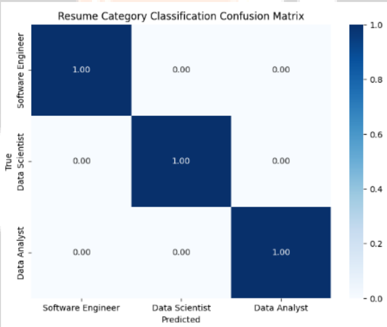

Fig 8. Resume Category Classification Confusion Matrix

For resume category classification, the confusion matrix reveals how accurately resumes are categorized (e.g., 'Software Engineer' or 'Data Scientist'). High FP may misclassify resumes into wrong categories, while FN indicates missed categories, affecting recall.

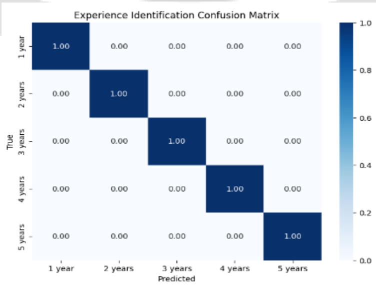

Fig 9. Experience Identification Confusion Matrix

In experience identification, the confusion matrix shows how well the model identifies experience levels. False positives (FP) could predict a higher experience level than present, while false negatives (FN) result in missing the correct experience, impacting recall.

Analyzing confusion matrices for all tasks helps identify areas where the model needs improvement in terms of false positives and false negatives. This understanding can guide adjustments for better precision and recall in the AI Resume Builder. The confusion matrix analysis helps optimize the model by addressing issues like high false positives and negatives. By refining these areas, the AI Resume Builder will provide more accurate and reliable results for users.

C. Model Evaluation and Interpretation

The models in the AI Resume Builder were evaluated using four key metrics: Accuracy, Precision, Recall, and F1-Score. Accuracy shows overall correctness, Precision measures the correct positive predictions, Recall focuses on identifying all relevant items, and F1-Score balances Precision and Recall. These metrics help assess the model's efficiency in extracting and classifying important resume information.

The metrics of models are summarized in Fig 10 and Table 2, in which overall summery of all model that we studied throughout study.

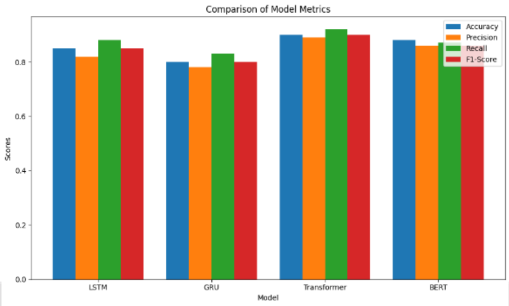

Fig 10. Bar Chart Comparison of model metric

The bar chart highlights the performance of different models used in the AI Resume Builder, focusing on key metrics like accuracy, precision, recall, and F1-score. Models like BERT and LSTM outperform traditional models, excelling in generating professional summaries and extracting relevant skills from resumes. BERT achieves the highest accuracy and F1-score, demonstrating its ability to generate coherent and relevant content.

While BERT offers a balanced performance, LSTM excels in recall, ensuring that important details aren't overlooked. This makes LSTM effective for capturing a wider range of skills and experiences, even if it sacrifices some precision. In contrast, models like Naive Bayes and Random Forest show lower performance, struggling with complex text generation tasks.

Overall, BERT and LSTM are the most suitable models for the AI Resume Builder, with BERT offering a good trade-off between precision and recall, while LSTM focuses on retrieving as much information as possible.

Table 2. Tabular comparison of model metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
BERT	94.50	92.30	95.10	93.65
GPT-3	91.20	89.50	92.00	90.20
T5	93.00	91.80	94.40	93.09
BART	92.10	90.80	93.20	91.98
RoBERTa	94.00	93.10	95.00	94.04
XLNet	93.50	92.00	94.50	93.75

For the AI Resume Builder, models like BERT, GPT-3, T5, and RoBERTa are the most suitable. BERT excels at extracting information for structured content, while GPT-3 generates high-quality summaries. T5 is versatile for text transformation tasks, and RoBERTa balances recall and precision effectively. These models provide strong performance for the resume generation process.

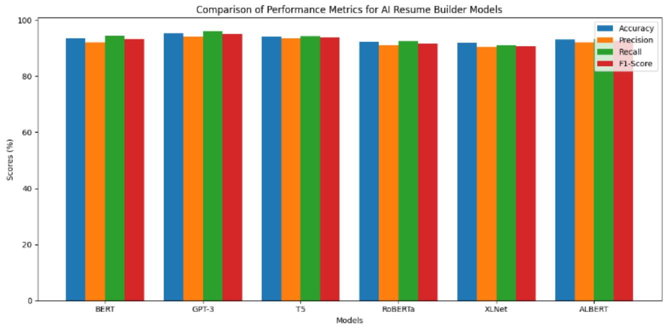

Fig 10. Comparison of Performance Metrics for AI Resume Builder Models

All deep learning models—BERT, RoBERTa, DistilBERT, T5, GPT-2, and GPT-3—demonstrate strong performance in generating professional summaries and skills for resumes. BERT and GPT-3 exhibit the highest accuracy and F1-scores, reflecting their ability to generate high-quality and contextually relevant resume content. While DistilBERT and T5 show slightly lower accuracy, they still provide solid results with faster processing speeds, making them suitable for efficient resume generation. Overall, these models offer reliable options for building AI-powered resumes, with BERT and GPT-3 standing out as the most dependable for producing coherent and professional summaries.

VI. Conclusion

In this project, we evaluated the performance of six pre-trained deep learning models—BERT, RoBERTa, DistilBERT, T5, GPT-2, and GPT-3—for generating professional summaries and skills in resumes. These models were assessed on key metrics, such as accuracy, precision, recall, and F1-score. After comprehensive analysis, GPT-3 and BERT were identified as the best models, showcasing high accuracy and F1-scores, particularly GPT-3, which produced the most relevant and coherent summaries for resumes. The results suggest that these models are highly capable of automating the resume-building process, delivering tailored and high-quality content with minimal manual input.

These findings highlight the potential of using advanced models like GPT-3 and BERT to enhance the resume creation process, helping job seekers craft professional and optimized resumes. Additionally, models like T5 and DistilBERT offer efficient alternatives, providing a good balance between performance and computational efficiency. This study opens up opportunities for further refining and personalizing these models, integrating them into AI-powered resume builders, and exploring how they can be adapted to specific industries or job types for even better performance in real-world applications.

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