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Job Tier Classification in Applicant Tracking Systems Utilizing One-Dimensional CNN

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Abstract. The increasing volume of job applications has made resume screening a critical yet challenging task for recruiters. Traditional Applicant Tracking Systems (ATS) often rely on keyword-based filtering, which may lead to inefficiencies and biases in candidate evaluation. This study proposes a One-Dimensional Convolutional Neural Network (1D CNN) model for job tier classification, utilizing TF-IDF embeddings and Named Entity Recognition (NER) to extract essential features from resumes. We specifically sought to evaluate the model's performance against conventional recruitment methods by comparing classification accuracy on labeled datasets comprising 1,444 resumes. The findings indicate that our approach achieved a 60.98% improvement in classification accuracy over traditional methods, with education being identified as the most significant predictor of job tier classification. However, limitations related to potential dataset biases and the reliance on automated evaluations are acknowledged. This research illustrates the potential for deep learning techniques to enhance recruitment automation, offering a scalable solution that may help reduce bias in resume classification within ATS.

Keywords: Applicant Tracking System, Resume Classification, Convolutional Neural Network, Natural Language Processing, Job Tier Prediction, Deep Learning, Named Entity Recognition, TF-IDF, Mutual Information

1. Introduction

The rapid expansion of the job market has resulted in a substantial influx of job applications, making it increasingly challenging for recruiters to efficiently process resumes. Applicant Tracking Systems (ATS) have emerged as a critical solution, leveraging automation to enhance the efficiency of resume screening. However, traditional ATS methods, primarily based on keyword matching and rule-based filtering, often fail to capture the contextual relevance of an applicant's qualifications, leading to biases and misclassification [1]. Moreover, manual resume screening remains a time-consuming process prone to human error, further emphasizing the need for automation [1].

Recent advancements in Applicant Tracking Systems (ATS) have leveraged deep learning and transformer-based models to enhance candidate evaluation. Technologies such as BERT and RoBERTa integrate Natural Language Processing (NLP) with structured learning models, leading to improved recruitment decisions [2]. Hybrid approaches that combine various AI techniques further enhance recruitment efficiency, automating processes from resume screening to onboarding [3].

Advancements in Natural Language Processing (NLP) and machine learning have significantly improved resume classification. Conventional machine learning techniques, such as Support Vector Machines (SVM) and Decision Trees, have been employed to enhance classification accuracy beyond simple rule-based approaches. However, these methods struggle with nuanced classifications due to their reliance on handcrafted features. In contrast, deep learning architectures, particularly Convolutional Neural Networks (CNNs), offer a more effective alternative by automatically extracting hierarchical features from textual data. [4]. Additionally, Sentence-Pair Classification models like Sentence-BERT utilize representation learning to match resumes with job descriptions more effectively than traditional keyword-based techniques [5].

Given these advancements, this study aims to explore the optimal configuration for CNN models in resume classification. Specifically, it seeks to develop a 1D CNN-based model to enhance automated resume screening and job tier classification. Additionally, the study investigates which features – such as education, skills, or work experience – play the most significant role in job tier classification. Understanding the importance of these features can help refine ATS systems for more accurate and fair candidate evaluation.

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Future research must focus on refining deep learning models to address these issues and further improve resume classification performance.

2. Literature Review

The evolution of Applicant Tracking Systems (ATS) marks a significant shift in recruitment technology, moving from early rule-based systems relying on keyword matching and Boolean searches [6] to modern AI-driven methodologies that incorporate Natural Language Processing (NLP) and Machine Learning (ML) [7][8]. This integration enhances resume screening by enabling a more holistic analysis of candidate profiles, leading to improved efficiency and a reduced time-to-hire [9]. Parallel to the advancements in ATS, automated resume classification techniques have also evolved. Initial rule-based methods, such as Boolean search and regular expressions [10], have given way to more sophisticated machine learning approaches. Early ML applications utilized Support Vector Machines (SVMs) and Decision Trees to improve classification accuracy through structured learning [11]. More recently, deep learning architectures, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have demonstrated enhanced capabilities in processing structured text for more effective resume screening [12][13]. These techniques, including SVMs and Decision Trees, analyze various resume attributes to improve candidate evaluation [14]. However, biases in recruitment models persist due to dataset imbalances and an over-reliance on specific attributes like education [15].

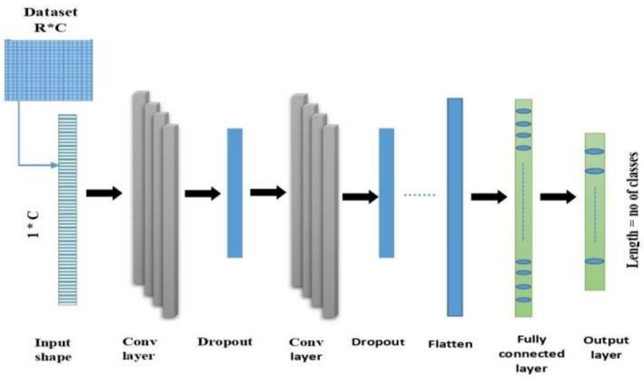

Fig. 1: Architecture of One-Dimensional CNN

One-dimensional Convolutional Neural Networks (1D CNNs) have emerged as a valuable tool for sequential text data processing in resume classification. Unlike traditional NLP models that depend on handcrafted features, 1D CNNs automatically extract patterns and relationships from raw text, facilitating efficient feature detection [16]. The architecture of a 1D CNN, involving convolutional layers for identifying key phrases and hierarchical features, followed by pooling layers for dimensionality reduction and fully connected layers for final classification (Fig. 1), has shown superior performance in resume categorization compared to traditional ML approaches [17]. While effective for local feature extraction, hybrid models combining CNNs with LSTMs or Transformers are being explored to further enhance contextual understanding in complex text analysis [18].

Finally, feature engineering plays a crucial role in optimizing machine learning models for resume classification. Traditional methods like word frequency analysis and Term Frequency-Inverse Document Frequency (TF-IDF) provide initial insights [19], while advanced techniques such as Named Entity Recognition (NER) and topic modeling significantly improve classification accuracy by extracting job-relevant entities and categorizing resumes based on job descriptions [20]. In job tier classification, careful analysis of key attributes such as education, experience, and skills is essential for determining candidate suitability. Feature selection techniques, including Mutual Information and Chi-Square, further refine model performance by identifying the most relevant features for classification [20].

3. Methodology

3.1. System Architecture

The proposed system utilizes a one-dimensional Convolutional Neural Network (1D CNN) to classify job applicants based on resume content. The system is designed to process textual resume data efficiently, extracting relevant information such as skills, education, and work experience. TF-IDF embeddings and Named Entity Recognition (NER) are incorporated to enhance feature extraction, ensuring that the model captures meaningful attributes necessary for job tier classification.

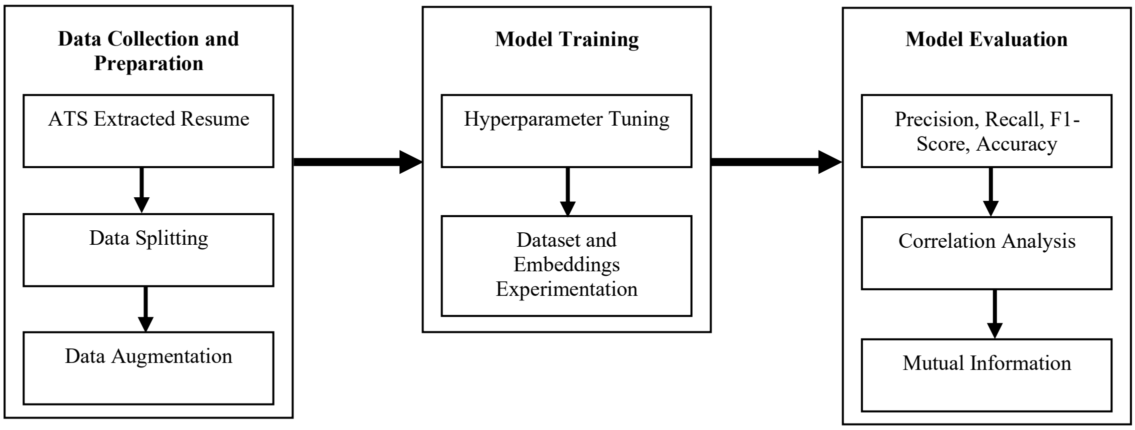

Fig. 2: System Architecture

3.2. Dataset Collection, and Preprocessing

The dataset for this study was collected from PDF and image-based resumes, categorized by job tiers. The dataset was processed by an Applicant Tracking System with automated information extraction. For PDF files, it was processed using pdfplumber, while image files used Tesseract OCR to extract text. Two datasets were prepared, D1 with 888 resumes and D2 with 556 resumes. Job tiers included BO (Back Office), CSA (Customer Service Associate), SA (Sales Associate), and TSA (Technical Support Associate). To balance the datasets, undersampling was applied.

Table 1: Datasets Classes and Distribution

Classes	Dataset 1 (D1)	Ratio	Dataset 2 (D2)	Ratio
BO	373	42.00%	139	25%
CSA	208	23.42%	139	25%
SA	168	18.92%	139	25%
TSA	139	15.65%	139	25%
Total	**888**	**~100%**	**556**	**100%**

Initial preprocessing involved cleaning the text by removing unnecessary characters, punctuation, and stopwords. Tokenization was performed to structure the text, and TF-IDF was used to convert resumes into numerical vectors. Named Entity Recognition (NER) helped extract key features like skills, education, and experience. Data augmentation techniques were also applied to increase dataset diversity and improve model generalization.

Each resume was organized with a unique ID, raw content (C2), cleaned content (C1), and labeled job tier. Extracted fields like skills, education, and work experience were included to enrich the dataset. Dataset balancing ensured fairness by maintaining an equal distribution across job tiers. This structured preprocessing created a solid foundation for effective model training and evaluation.

3.3. Hyperparameter Tuning

Table 2: CNN Parameters per Model

Feature	Model 1 (1D CNN)	Model 2 (7-layer CNN)
Depth	Shallow (1 Conv1D layer)	Deep (3 Conv1D layers)
Filters	64 filters	256 filters per Conv layer
Kernel Sizes	Fixed (3)	Varying (3, 5, 7) for multi-scale features
Pooling	MaxPooling	Global MaxPooling
Embedding	Not present	Present (for text data)
Dropout	0.5 (higher regularization)	0.3 (lower regularization)

To find the best setup for text classification, two CNN architectures were evaluated; a shallow 1D **CNN (Model 1)** and a deeper **7-layer CNN (Model 2)**. Model 1 featured a single Conv1D layer with 64 filters, a fixed kernel size of 3, MaxPooling, and a dropout rate of 0.5 for strong regularization. Model 2 was deeper, with three Conv1D layers each using 256 filters and varying kernel sizes (3, 5, and 7) to capture multi-scale features. It uses Global MaxPooling for better long-range pattern detection and a lower dropout rate of 0.3.

Both models were tested under different dataset conditions**; D1 (imbalanced) and D2 (balanced by undersampling)**. Text data was also prepared in two forms: **C1 (cleaned) and C2 (raw)**. Data augmentation was optionally applied to increase training samples, and two vectorization methods were explored; TF-IDF and GloVe embeddings.

Each experiment involved tweaking hyperparameters to optimize resume classification. Results showed how various combinations of dataset preparation, augmentation, and model architecture influenced performance, helping identify the most effective configuration for text-based classification tasks.

3.4. Feature Selection

To enhance the model's performance, Mutual Information (MI) classifier was used to identify the most informative features – those that had the strongest relationship with the target outcome. This step ensured that only the most relevant attributes were retained, reducing noise and improving overall efficiency. Mutual Information measures the dependency between two variables, where a higher MI value indicates a stronger relationship. If MI is zero, it means the variables are completely independent and provide no useful information about each other.

In this study, three key factors were considered for feature selection; **Skill** – The specific competencies and expertise extracted from resumes. **Education** – The candidate's academic background and qualifications. **Work Experience** – The professional history, including roles and tenure.

By evaluating the mutual information between these features and the classification target, the most impactful attributes were prioritized. This process helped the model focus on the most predictive elements, improving accuracy while reducing computational complexity.

3.5. Evaluation Metrics

The model's performance was evaluated using precision, recall, and F1-score to assess how well it classified resumes into appropriate job tiers. These metrics helped determine the model's reliability in making accurate classifications.

A confusion matrix was used to analyze classification results:

- True Positives (TP): Resumes correctly assigned to the appropriate job tier.
- False Positives (FP): Resumes incorrectly assigned to a higher or different job tier.
- False Negatives (FN): Resumes that should have been classified under a job tier but were missed.
- True Negatives (TN): Resumes correctly identified as not belonging to a specific job tier.

By focusing on these core evaluation metrics, the study ensured a balanced assessment of both the model's accuracy and its ability to generalize effectively across different resume classifications.

4. Results and Discussions

4.1. CNN Best Configuration

The study explored 32 CNN model variations to identify the best setup for resume classification. The optimal configuration used a balanced dataset (D2), cleaned text (C1), augmentation, TF-IDF embeddings, and a 1D CNN, achieving 60.98% accuracy, 63.42 precision, 62.50 recall, and an F1-score of 62.96.

Balanced datasets significantly improved performance, with D2 outperforming D1 due to reduced bias across job tiers. Shallower CNNs (3–5 layers) generalized better than deeper models, which showed signs of overfitting despite higher training accuracy.

Data augmentation boosted recall and F1-score but slightly reduced precision. TF-IDF embeddings yielded better results than GloVe, which struggled with recall due to their static nature. Trade-offs were observed: high-precision models tended to miss relevant resumes (low recall), while higher-recall models made more misclassifications—highlighting the balance between conservative and inclusive predictions in classification tasks.

4.2. CNN Compared to Other Models

The 1D CNN model demonstrated superior performance in job tier classification compared to BERT and traditional machine learning models, suggesting its effectiveness in extracting relevant features from resume text. For instance, the 1D CNN achieved an accuracy of 60.98%, which represents a significant improvement over BERT's 48.78% and the traditional models, which ranged from about 51% to 56%. This translates to the 1D CNN performing approximately 5-12% better in accuracy than the traditional models, and over 12%

better than BERT. While BERT underperformed, possibly due to the nature of the task or limitations in data or fine-tuning, traditional models offered a moderate baseline. These findings highlight the potential of CNNs for enhancing resume screening and recruitment automation, underscoring the importance of model architecture and feature engineering in this application.

Table 3: CNN vs BERT vs Traditional Models

Model	Accuracy	Precision	Recall	F1-Score
1D CNN	**60.98**	**63.42**	**62.50**	**62.96**
BERT	48.78	43.26	44.32	43.26
Random Forest	56.1	56.45	56.1	56.09
SVM	53.66	53.25	53.66	53.17
Gradient Boosting	51.77	48.78	49.57	51.77

4.3. Mutual Information (MI) Classification

Table 4: Mutual Information Classification Relevance

Entity	Skill Relevance	Education Relevance	Work Exp Relevance
BO	0.0589	0.0846	0.0214
CSA	0.0658	0.0699	0.0165
SA	0.0683	0.0850	0.0240
TSA	0.0480	0.0740	0.0218

Feature selection using Mutual Information (MI) analysis was conducted to measure the dependency between features and job tiers. The results revealed a clear hierarchy of feature importance, with education showing the highest relevance in job classification. This suggests that academic background plays a significant role in determining job placement. Skills had moderate importance, indicating their influence but not dominance in classification. In contrast, work experience had the lowest impact across all job tiers, suggesting that prior job history is less predictive than education and skills in this context.

Table 4 shows that Sales Associate (SA) roles had the highest MI relevance for skills (0.0683) and education (0.0850), emphasizing their importance in classification. Conversely, Technical Support Associate (TSA) roles had the lowest skill relevance (0.0480), suggesting broader qualifications beyond specific skills. For this classification task, the best-performing model configuration, identified through CNN hyperparameter tuning, was applied. This setup used the best model configuration and the results confirming that education is the most significant factor in classification. These findings reinforce that education plays a dominant role in job tier classification, while skills provide additional value and work experience has minimal influence in this model.

5. Conclusion

This study developed a 1D CNN-based job tier classification model that uses TF-IDF embeddings and NER to automate resume screening within an ATS. The optimal setup—balanced, undersampled data with 1D CNN—achieved the best accuracy while supporting fairer classification. Results show that education is the most influential factor in classification, followed by skills, with work experience having the least impact, as confirmed by Mutual Information analysis. While CNNs significantly improve efficiency beyond keyword-based methods, challenges like data bias and limited interpretability highlight the need for human oversight. The model shows strong potential but requires validation from HR professionals to assess usability, acknowledging that human judgment remains essential in final hiring decisions.

6. Recommendations

To improve generalizability, future work should apply advanced balancing techniques such as SMOTE or cost-sensitive learning. Developing hybrid models that combine CNNs with transformers may improve classification accuracy by leveraging both local and long-range text patterns. Real-world deployment within ATS platforms is also encouraged to assess performance, identify bias, and incorporate recruiter feedback for fairer, more context-aware hiring solutions.

Finally, deploying this model in a real-world Applicant Tracking System (ATS) would provide critical insights into practical challenges, including real-time performance evaluation, bias detection, and recruiterdriven refinements. This would ensure AI-driven hiring systems become not only more efficient and scalable but also fairer and more contextually aware in screening resumes and selecting candidates.

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