International journal of imaging science and engineering

ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025

AI-Powered Job Market Insights to Predict Future Demand for Skills Across Various Job Markets

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Abstract:

In today's rapidly evolving job market, the demand for specific skills has seen substantial shifts, with reports indicating that 85 million jobs are expected to be displaced by 2025 due to automation and technological advancements. Conversely, approximately 97 million new roles may emerge, emphasizing the need for a proactive approach to skill development. Despite these shifts, many job seekers and educators still rely on outdated information and anecdotal evidence to gauge which skills will be relevant in the future job market. The proposed AI Powered Job Market Insights system aims to address these challenges by utilizing multi-variate deep learning classification to analyze job postings, industry trends, and economic data to predict future skill demand across various job markets. The system employs preprocessing techniques such as data cleaning, normalization, and feature extraction to enhance the quality of input data. By classifying essential skills like "Python," "Data Analysis," and "Project Management," alongside projecting job growth as "Decline," "Stable," or "Growth," this research seeks to provide a comprehensive tool for job seekers, educational institutions, and policymakers to make informed decisions based on predictive analytics.

Keywords: Job Market, Automation, Skill Development, Deep Learning, Classification, Job Postings, Predictive, Analytics Feature, Extraction Economic Data, Industry Trends, AI-Powered Preprocessing, Normalization, Job Growth, Policymakers

1. INTRODUCTION

The job market landscape is undergoing significant changes, with skill demand fluctuating due to technological innovations and economic shifts. According to the World Economic Forum, by 2025, approximately 44% of the skills that workers will need to perform their jobs effectively will change. This shift highlights the necessity for continuous learning, adaptability, and proactive skill development to remain competitive in the workforce.

One of the major drivers of this transformation is the increasing reliance on advanced technologies such as artificial intelligence (AI), automation, and data analytics. These innovations are reshaping industries, creating new roles, and making others obsolete. In the U.S. alone, the Bureau of Labor Statistics predicts a 10.1% growth in jobs requiring advanced technological skills over the next decade. This rapid shift underscores the importance of gaining accurate insights into skill demand so that workers, employers, and educators can make informed decisions about workforce development.
Despite the growing demand for specialized skills, many workers and job seekers struggle to keep pace with evolving industry requirements. The rapid rate of change can create skill gaps between education and employment, leading to underemployment and mismatches in the labor market. Recent reports indicate that nearly 50% of employers face difficulties in finding candidates with the necessary skills to meet job demands. This talent shortage highlights the pressing need for modern tools and resources that can help bridge this gap and better align workforce training with emerging job market trends.
To address these challenges, a more data-driven approach to workforce planning is essential. AI-powered systems that analyze job postings, industry trends, and economic data can help predict future skill requirements. By leveraging machine learning algorithms, these systems can identify high-demand skills, classify them into relevant job categories, and forecast job growth patterns. Such insights would be invaluable for job seekers aiming to upskill, educational institutions designing curriculum improvements, and policymakers shaping workforce development strategies.
Ultimately, understanding the future demand for specific skills is crucial in ensuring that workers remain employable in an ever-changing job market. By proactively addressing skill gaps and aligning education with industry needs, we can create a more resilient and future-ready workforce.

2. LITERATURESURVEY

Research by Bick et al. [1] indicates that 60% of occupations have at least 30% work activities that could be automated. Automation has triggered a growing demand for technical skills such as data analysis, artificial intelligence, and machine learning, while offshoring amplifies the relevance of intercultural communication and global collaboration skills. Eloundou et al. [2] investigated the impact of LLMs such as GPT and BLOOM on the labor market. They note that routine and repetitive tasks have a high risk of technology-driven displacement. Brynjolfsson et al. [3] distinguish between the labor-augmenting and labor-displacing effects of automation use exposure as the main factor in their automation risk classification. They consider three cases: no exposure (e.g., minimal or no time reduction for completing a task using an LLM or software agent), direct exposure (e.g., LLMs reduce task completion times by 50 percent), and indirect exposure. Pinheiro et al. [4] conducted a meta-regression analysis of the published research. They analyze four major automation trends (cost advantage, increased productivity, robots, and Industry 4.0) and their influence on offshoring and reshoring. Wagner. et al work [5] on digital talent platforms (e.g., Freelancer, Upwork and Fiveer) provided important insights towards preparing the offshorable task gold standard. Digital talent platforms help employers meet unplanned needs for knowledge work services lower the need for permanent positions by hiring specialized workers for specific contracts. Lipsey.et al [6] conducted a meta-regression analysis of the published research. They analyze four major automation trends (cost advantage, increased productivity, robots, and Industry 4.0) and their influence on offshoring and reshoring. A large-scale survey by Minaee et al. [7] presents most of the deep learning architectures widely used for text classification, from LSTMs to Transformers. A taxonomy of Transformers can be found in and includes most models used for classification until late 2021. Khaouja et al. [8] distinguish three different levels of skill label granularity: and sentences (e.g., “Experience in software development, particularly the development of Java Web applications.”). The presented approach draws upon German bipartite skill labels that are part of a proprietary occupation knowledge base which formalizes domain knowledgein the human resources domain. Josten. et al [9] classified O*NET professions based on their degree of automatability (e.g., full, non-, or partial). The main goal of their work was better alignment with the European labor force survey, accessed on 1 March which covers the period between 2013 and 2016. Based on a regression analysis, they established that occupations that require brains (e.g., abstract reasoning) are better protected from automation, especially when compared to occupations that require daily interaction (e.g., people skills) and physical interaction (e.g., brawn). Combining these factors can also decrease the likelihood of automation. Dunn. et al [10] classifies Gig economy platforms into: (i) low-skill (e.g., Uber, Bold, TaskRabbit) or high-skill location-dependent (e.g., Outschool or Tutoroo for private lessons) and (ii) low-skill (e.g., Amazon Mechanical Turk) or high-skill (e.g., Fiverr and Upwork) location-independent services. These services can be used as starting points for assessing offshorability, as all the tasks listed in their catalogs have already been offshored successfully. Bommasani. et al [11] even names pre-trained Transformer foundation models because most NLP tasks can be designed around them. Still, they also require adaptation to domain-specific tasks (e.g., text classification, sentiment analysis, etc. Pham et al. [12]. Another recent survey examines text classification models in the context of designing spam filters.

3.PROPOSED METHODOLOGY

The AI-powered job market insights system is designed to analyze job market trends and predict future demand for skills using multi-variate deep learning classification. By leveraging advanced machine learning techniques, the system identifies evolving workforce requirements and provides valuable insights for job seekers, recruiters, and policymakers. The implementation of predictive modeling enhances career planning, enabling individuals to align their skill development with future industry needs. As technological advancements continue to reshape employment landscapes, understanding which skills will be in demand is essential for ensuring workforce readiness and economic stability. The system processes vast amounts of job-related data, extracting key features and applying deep learning models to forecast the demand for specific skills. Through a combination of natural language processing (NLP) and structured data analysis, it delivers precise, data-driven insights that help individuals and organizations stay ahead of changing job market trends. By analyzing historical and real-time job postings, the system identifies patterns in industry demands, highlighting emerging skills and declining roles. This enables job seekers to make informed decisions about career development while helping recruiters and employers find candidates with the right expertise. A crucial component of this system is feature engineering, which structures and processes job market data to enhance the efficiency and accuracy of machine learning model training. The implementation of deep learning techniques, including convolutional neural networks (CNN) and gradient boosting classifiers (GBC), further refines prediction accuracy, ensuring reliable and actionable insights. Additionally, the system provides industry-specific insights, offering a sector-wise analysis to help job seekers, employers, and educators understand domain-specific skill requirements. By tailoring recommendations to particular industries, such as healthcare, information technology, finance, and manufacturing, the system ensures that workforce development efforts align with actual market needs. To maximize accessibility and usability, the system is deployed as an interactive platform, serving as a decision support tool for professionals, recruiters, and policymakers. This platform allows stakeholders to access market-driven insights, aiding in workforce planning, talent acquisition, and policy formulation. One of its key strengths is its ability to provide real-time updates, continuously integrating new job market data to refine predictions over time. As industries evolve and new technologies emerge, the system adapts accordingly, ensuring that its insights remain relevant and up to date. By offering accurate skill demand predictions and real-time job market analysis, this AI-powered system plays a pivotal role in bridging the gap between education and employment. It empowers job seekers with the knowledge needed to enhance their employability, supports recruiters in identifying qualified talent, and assists policymakers in designing workforce development initiatives that align with future labor market needs. Through continuous learning and adaptability, this system ensures that individuals and organizations remain prepared for the dynamic and ever-evolving job market.

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ISSN: 1934--9955 www.ijise.net
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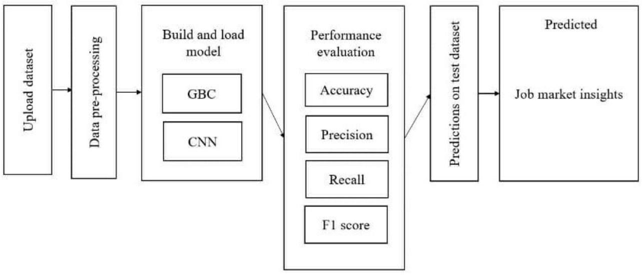


Figure 1: Proposed block diagram

Applications:

Applications of the AI-Powered Job Market Insights System: Career Guidance and Skill Development

- Career Guidance and Skill Development – Assists job seekers in identifying emerging skills and planning career growth accordingly.
- Recruitment and Talent Acquisition – Helps recruiters and HR professionals find candidates with the right skills based on data-driven insights.
- Workforce Planning for Policymakers – Supports government agencies in designing employment policies and workforce development strategies.
- Educational Curriculum Development – Guides universities and training institutions in updating courses to match industry demands.
- Corporate Workforce Strategy – Enables businesses to predict skill gaps and invest in employee upskilling programs.
- Freelancing and Gig Economy Insights – Helps independent workers identify high-demand skills to improve job opportunities.
- Economic and Industry Trend Analysis – Provides insights into job market fluctuations and economic impacts on employment.
- Diversity and Inclusion in Hiring – Assists organizations in creating fair and data-driven hiring strategies for diverse talent pools.
- Job Market Forecasting for Startups – Helps new businesses understand hiring trends and plan workforce needs efficiently.
- Personalized Learning Pathways – Recommends courses and certifications based on an individual's career aspirations and market trends

Advantages:

- Uses deep learning to predict emerging skills and future job market trends.
- Continuously processes real-time and historical job postings for accurate insights.
- Helps job seekers align their skills with evolving industry demands.
- Provides industry-specific insights to help professionals understand sector-based requirements.
- Assists recruiters in identifying qualified candidates through data-driven analysis.
- Bridges the gap between education and employment by aligning training programs with market needs.
- Ensures accessibility with an interactive and user-friendly platform for all stakeholders.
- Supports policymakers and organizations in workforce planning with reliable market insights.
- Utilizes advanced machine learning models like CNN and GBC to enhance prediction accuracy.
- Regularly updates with new job market data to ensure continuous learning and adaptability.
- Helps businesses and governments anticipate workforce demands, boosting economic growth. Identifies emerging job roles created by technological advancements and industry shifts.
- Enables companies to address skill shortages and implement effective employee training programs.
- Provides unbiased, data-driven hiring recommendations to enhance diversity and inclusion.
- Helps freelancers and gig workers identify high-demand skills and project opportunities.

4. EXPERIMENTAL ANALYSIS

Figure 2 shows the count plot of the categories. A countplot is used in this project to visualize the distribution of the job growth projection categories, helping to understand how the target variable (Job_Growth_Projection) is distributed across different classes (Growth, Stable,

Decline).

Figure 2: Uploading dataset

Figure 3 shows the count plot of the categories. A countplot is used in this project to visualize the distribution of the job growth projection categories, helping to understand how the target variable (Job_Growth_Projection) is distributed across different classes (Growth, Stable, Decline).

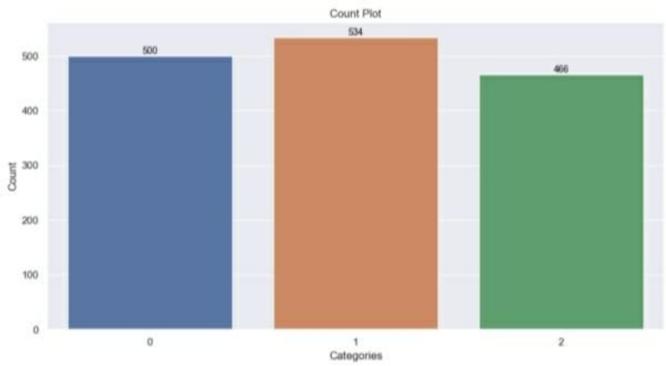


Figure 3: Count Plot for the categories

Figure 4 shows the correlation heatmap is used in the project to analyse the relationships between different numerical features and understand their impact on job growth projection. The heatmap uses correlation coefficients (Pearson's correlation) to measure the linear relationships between numerical features. By analysing the heatmap, we can refine feature selection and improve model performance for predicting future job.

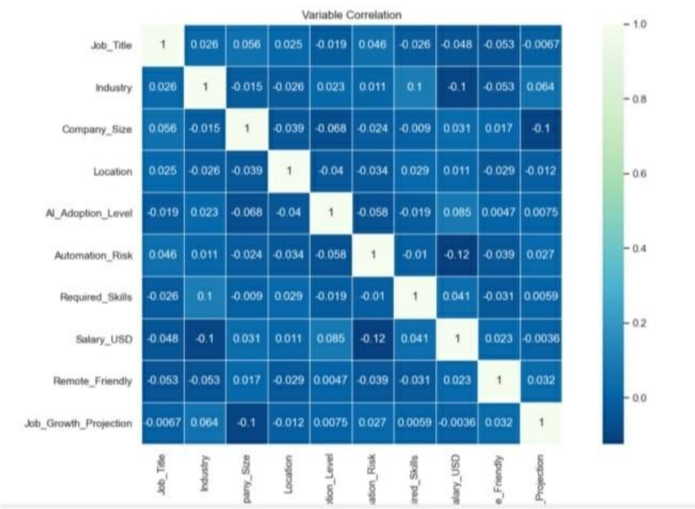
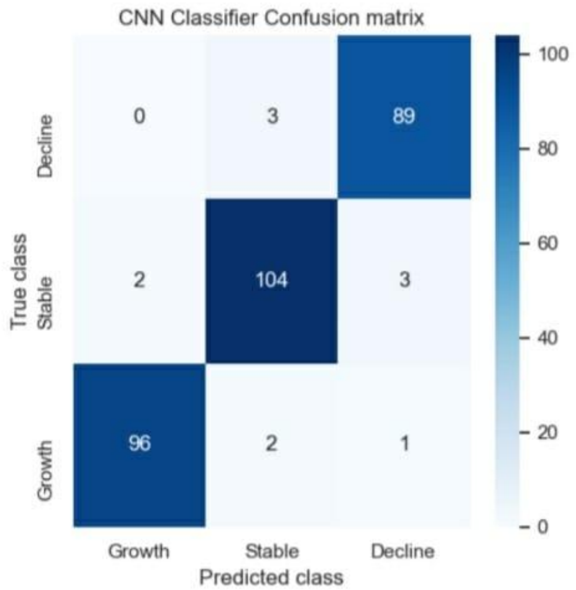


Figure 4: Correlation heatmap

A confusion matrix is a common tool for evaluating the performance of a classification model. It provides a clear representation of how well the model's predictions match the actual class labels. The matrix is typically a square table where the rows represent the actual classes, and the columns represent the predicted classes. Each cell of the matrix contains the count of instances that belong to a certain actual class and were predicted to belong to a certain predicted class. From Figure 10.5, it visually depicts the confusion matrix obtained from the GBC model's



predictions, helping to assess the model's accuracy, precision, recall, an

Figure 2: Illustration of confusion matrix

5. CONCLUSION

The AI-powered Job Market Insights System effectively predicts future job demand by analyzing various factors such as skill importance, salary trends, and automation risks. Utilizing multi-variate deep learning classification, the model generates accurate insights into emerging job opportunities and declining roles. By integrating correlation analysis and feature engineering, the system identifies key trends shaping employment growth, ensuring a comprehensive understanding of workforce dynamics.

The findings indicate that skills related to AI, data science, and automation have strong positive projections, reflecting the increasing demand for technology-driven expertise. Conversely, jobs with high automation risks are projected to decline, highlighting the impact of technological advancements on employment.

These insights are essential for job seekers looking to align their skills with future opportunities, employers aiming to hire talent in high-growth areas, and policymakers developing workforce strategies to address labor market shifts.

The system also enhances career planning by offering data-driven guidance on skill acquisition and job market trends. By continuously processing large volumes of job-related data, it ensures that recommendations remain relevant and up to date. Additionally, its interactive platform provides accessibility to professionals, recruiters, and decision-makers, helping them make informed choices about employment and industry needs. Overall, the AI-powered system serves as a valuable tool for workforce development, bridging the gap between education and employment while enabling individuals and organizations to adapt to an evolving job market.

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