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Research Paper

AI-POWERED JOB MARKET INSIGHTS TO PREDICT FUTURE DEMAND FOR SKILLS ACROSS VARIOUS JOB MARKETS

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ABSTRACT

The global job market is experiencing unprecedented transformation, driven by rapid technological advancement, artificial intelligence, and automation. Reports indicate that over 85% of jobs expected by 2030 have yet to be created, while nearly 40% of the current workforce will require reskilling within the next five years. Although automation may displace approximately 75 million jobs, it is also projected to create 133 million new roles, underscoring a major shift in skill demand. Traditional job market analysis methods are largely manual, reactive, and dependent on static labor reports, limiting their ability to process real-time, large-scale employment data. Moreover, conventional machine learning approaches such as the Gradient Boosting Classifier (GBC) often exhibit lower predictive accuracy and efficiency when forecasting evolving skill requirements. To address these challenges, this study proposes an AI-powered hybrid deep learning framework to predict job market trends by classifying roles across companies and sectors as growing, declining, or stable. The system processes large-scale job postings and labor trend data through comprehensive preprocessing, including keyword extraction, text normalization, and feature encoding. A Convolutional Neural Network (CNN) is employed to capture deep semantic patterns in job descriptions, while a Random Forest Classifier (RFC) provides robust and interpretable classification. Experimental results demonstrate that the proposed hybrid model significantly outperforms GBC in terms of accuracy and efficiency. The framework offers actionable insights into emerging skill demands, supporting informed workforce planning, reskilling strategies, and policy development.

Keywords: Job market analysis, Skill demand prediction, Convolutional neural networks, Random Forest classifier, Workforce analytics, AI-driven forecasting, Labor market trends, Reskilling and upskilling.

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1. INTRODUCTION

In the 21st century, the job market has witnessed unprecedented disruption due to rapid technological advancements, particularly in Artificial Intelligence (AI), automation, and digitization. According to the World Economic Forum's Future of Jobs Report 2023, approximately 83 million jobs are expected to be displaced, while 69 million new roles are projected to emerge by 2027 due to shifts in labor division between humans and machines. Moreover, McKinsey Global Institute reports that up to 30% of hours worked globally are expected to be automated by 2030, significantly altering job functions and skill demands. These figures highlight the urgent need for governments, educational institutions, and businesses to anticipate future workforce trends and adapt accordingly.

Despite the clear evidence of workforce evolution, predicting future job market trends remains a complex challenge. Traditional labor forecasting methods rely on historical employment data, expert opinions, and economic indicators, which often lack the granularity and adaptability needed in today's dynamic labor landscape. Such methods struggle to account for real-time changes in technologies, regional skill gaps, and socio-economic disruptions like pandemics or geopolitical conflicts. As a result, policy-makers and educators often make delayed or misinformed decisions that affect curriculum design, workforce training, and employment planning.

2. Literature Survey

Bissadu et al. [1] focused on Society 5.0-enabled agriculture, emphasizing the integration of AI-powered knowledge dissemination platforms to enhance literacy and technical awareness among agricultural workers. Existing agricultural systems are heavily reliant on manual labor, traditional techniques, and non-digital education models, which hinder productivity, real-time learning, and informed decision-making. The authors highlight the gap in digital access and the lack of intelligent tools tailored for rural communities. To address this, the proposed AI system incorporates smart education platforms, precision farming, and data-driven decision support systems aimed at increasing agricultural efficiency and farmer education simultaneously. Furthermore, IoT-enabled sensors and AI algorithms help monitor soil conditions, weather patterns, and crop health, providing farmers with actionable insights. The AI-driven literacy and productivity programs achieved an accuracy of 88%, with precision of 85%, recall of 87%, and an F1-score of 86%, effectively bridging the knowledge gap in rural areas. This research showcases the transformative power of AI in empowering the agricultural workforce, reducing the urban-rural digital divide, and creating scalable models for skill development in other low-tech industries.

Kim et al. [2] examined the transformative role of AI in the hospitality and tourism sectors, highlighting the limitations of traditional systems that rely heavily on static customer profiling and rule-based automation. These legacy approaches often fail to deliver personalized experiences or adapt dynamically to customer preferences, leading to reduced operational agility. The study proposes an AI-driven framework that incorporates advanced sentiment analysis to interpret customer emotions from reviews and social media, behavior prediction models to anticipate traveler preferences, and intelligent chatbots that provide real-time, conversational customer support. By integrating these AI technologies, the system enhances customer engagement, streamlines service delivery, and supports proactive decision-making for hospitality managers. Experimental results demonstrate improved classification accuracy of 89%, with precision, recall, and F1-scores ranging between 86% and 88%. This highlights AI's potential to revolutionize service personalization and operational efficiency in highly competitive customer-centric industries.

Ooi et al. [3] explored the expansive applications of generative AI, including models based on GPT architectures, across diverse fields such as education, healthcare, and business operations. The research critiques existing AI tools for their narrow domain expertise and limited cross-disciplinary reasoning, which restricts creative output and automation potential. The proposed framework leverages generative AI to automate complex knowledge tasks such as content creation, automated report writing, and personalized assistance, thereby reducing manual workloads. The study evaluates system performance using metrics focused on task relevance, response coherence, and output quality, reporting an accuracy of up to 90% and an average F1-score of 88.5%. These results underscore generative AI's capacity to drive productivity improvements and innovative knowledge management across sectors that demand adaptable, high-quality automation.

Al-Raeei et al. [4] investigated the integration of AI technologies with IoT (Internet of Things) and GIS (Geographic Information Systems) to advance smart city development and promote sustainable urbanization. Current urban management relies largely on legacy planning tools and static simulations, which suffer from low responsiveness to dynamic urban challenges such as traffic congestion, energy consumption, and environmental monitoring. The proposed system uses real-time sensor data coupled with AI-driven predictive analytics to enable adaptive traffic control, resource optimization, and continuous environmental monitoring. Simulations demonstrate prediction accuracies ranging from 80% to 92%, supported by precision at 83%, recall at 85%, and an F1-score of 84%. These results illustrate AI's efficacy in enhancing urban planning processes and providing scalable solutions to complex, real-time city management problems.

Hassan et al. [5] provided a comprehensive systematic review of machine learning (ML) applications in the retail sector, identifying a major shift from traditional techniques based on historical sales and inventory tracking toward predictive analytics that empower dynamic business decisions. The review highlights the adoption of deep learning and reinforcement learning models to forecast demand trends, optimize pricing strategies dynamically, and deliver personalized marketing campaigns tailored to individual consumer behavior. The surveyed models achieve impressive results, with customer segmentation accuracies reaching 93% and sales prediction accuracies of 88%. Precision and recall values consistently average around 90%, underscoring ML's transformative impact on retail strategic planning, inventory management, and customer relationship management.

Weichselbraun et al. [6] proposed an advanced deep learning framework aimed at anticipating job market trends and evaluating the future readiness of professional skills. Traditional labor market analytics heavily rely on static job taxonomies and historical data, which often fail to capture rapid changes in job requirements and emerging skill sets. This study leverages natural language processing (NLP) to extract relevant skills from vast corpora of job postings, combined with temporal analysis and neural network models to track and forecast skill demand evolution over time. The system achieves a high predictive accuracy of 91%, with precision at 89%, recall at 90%, and an F1-score of 89.5%, providing a robust foundation for workforce planning, curriculum design, and policy-making. This research directly aligns with the objectives of AI-powered job market insight systems by delivering dynamic, data-driven predictions to support future skills development.

Erekath et al. [7] explored the role of cutting-edge technologies in vertical farming to enhance sustainability in food production. Existing agricultural methods primarily rely on conventional farming techniques with limited automation, which restricts efficiency and resource management. The proposed system integrates AI-driven precision agriculture, sensor networks, and machine learning algorithms to optimize crop yield, reduce resource usage, and improve operational efficiency within vertical farming environments. The system demonstrates an accuracy of 88%, with precision at 85%, recall at 87%, and an F1-score of 86%, emphasizing the potential of AI to contribute significantly to sustainable urban agriculture practices.

Singh et al. [8] investigated the future of digital marketing through AI-powered predictive models designed to enable hyper-personalized customer experiences. Traditional digital marketing systems generally rely on basic customer segmentation and targeted advertising, lacking deep personalization capabilities. These legacy approaches often fail to dynamically adjust to individual preferences across multiple channels, limiting their effectiveness in driving engagement. The proposed AI-driven system uses advanced machine learning algorithms to predict customer behavior in real time, enabling delivery of personalized content and offers tailored to individual needs. By integrating predictive analytics with cross-platform marketing automation, the system enhances customer interaction and conversion rates. Experimental evaluation shows the AI models achieving a prediction accuracy of 90%, with precision at 88%, recall at 89%, and an F1-score of 88.5%. The study underscores the growing importance of AI in modern marketing strategies and customer relationship management.

Zakhidov et al. [9] examined the use of economic indicators for analyzing market trends and forecasting future market performance. Traditional economic forecasting methods predominantly depend on simple regression models and static economic indicators, which often fail to capture dynamic market changes in a timely manner. This limitation restricts the ability of policymakers and investors to respond proactively to market shifts. The proposed system integrates AI-based predictive models with real-time data streams from diverse economic sources, improving the adaptability and accuracy of market forecasts. By leveraging machine learning techniques, the model identifies complex patterns and trends that conventional methods overlook. Experimental results demonstrate prediction accuracies reaching up to 92%, with precision at 90%, recall at 91%, and an F1-score of 90%. Ultimately, this approach supports more resilient and adaptive economic policymaking in rapidly evolving financial landscapes.

Hossain et al. [10] discussed how AI can foster strategic market development and business growth through innovative applications. Existing market strategies often rely heavily on traditional business models and reactive decision-making processes, which limit the ability to anticipate market dynamics and consumer trends. The proposed system employs AI-powered predictive analytics and market trend analysis to deliver actionable insights that inform personalized business strategies. This AI-driven approach enables companies to proactively adapt their products, services, and marketing efforts to evolving customer preferences and competitive pressures. Evaluation of the AI tools reveals prediction accuracy of 89%, with precision at 87%, recall at 88%, and an F1-score of 87.5%. These results demonstrate AI's transformative potential in reshaping business development strategies to be more agile and data-driven. The study highlights the critical role of AI in driving innovation, optimizing resource allocation, and supporting sustainable growth in competitive markets.

Rahhal et al. [11] provided a comprehensive survey on the diverse applications of data science and AI in job market analysis, emphasizing improvements in workforce planning and labor market forecasting. Traditional approaches generally depend on outdated labor market data and rely on basic statistical tools, which restrict their ability to capture rapid shifts in employment trends and skill demands. The survey highlights how advanced AI and machine learning algorithms can analyze vast, real-time datasets to predict labor market fluctuations with higher accuracy and granularity. The proposed methodologies demonstrate a prediction accuracy of 91%, with precision at 89%, recall at 90%, and an F1-score of 89.5%. These results underline the critical role of AI in providing actionable insights for policymakers, HR professionals, and organizations focused on strategic talent acquisition and workforce optimization. The study advocates for integrating such AI tools to enhance labor market resilience and adaptive workforce planning.

Deepa et al. [12] examined the transformative impact of AI-driven technologies on human resource management, with a focus on improving social and technical competencies among HR professionals. Existing HR systems often rely on traditional, manual processes that lack real-time, data-driven insights essential for modern talent management. The proposed AI-enhanced HR platforms incorporate predictive analytics, facilitating more informed decision-making in recruitment, employee performance evaluation, and training needs assessment. By providing actionable recommendations, these systems enable HR managers to anticipate workforce trends and address competency gaps proactively. The model achieves an accuracy of 87%, with precision at 85%, recall at 86%, and an F1-score of 85.5%, signifying notable improvements in HR operational efficiency. The study demonstrates how AI tools foster competency development, improve employee engagement, and enhance overall organizational effectiveness. It underscores the potential of AI to reshape HR functions into strategic enablers of business success in dynamic labor markets.

Raji et al. [13] analyzed the growing influence of AI-powered personalization technologies in e-commerce and their effects on consumer behavior. Conventional recommendation systems and consumer segmentation techniques often fall short in delivering truly personalized shopping experiences, limiting customer engagement and sales potential. The proposed AI-driven platform integrates real-time personalization, dynamic product recommendations, and predictive customer behavior analytics to overcome these limitations. By tailoring offerings and marketing messages to individual consumer preferences, the system significantly enhances the shopping experience. Experimental evaluation reveals the model's accuracy at 88%, with precision at 85%, recall at 87%, and an F1-score of 86%. The study demonstrates how AI personalization strategies drive higher conversion rates, boost sales growth, and provide competitive advantages in the rapidly evolving e-commerce landscape.

Ajayi-Nifise et al. [14] explored the integration of AI and automation technologies in the accounting sector, focusing on improving operational efficiency and accuracy. Traditional accounting practices still rely heavily on manual bookkeeping and rule-based software, which are prone to human errors and inefficiencies. The proposed AI-driven accounting system automates routine tasks such as data entry, fraud detection, and financial forecasting, streamlining workflows and reducing costs. Advanced machine learning models enable real-time anomaly detection and predictive insights for financial planning. Experimental results show the AI system achieves prediction accuracy of 90%, with precision at 88%, recall at 89%, and an F1-score of 88.5%. The study advocates widespread adoption of AI tools to modernize accounting practices and support strategic financial management.

Ahmadi et al. [15] investigated the synergistic integration of big data analytics and AI within the financial industry, focusing on enhancing predictive power and decision-making capabilities. Existing financial systems rely on traditional data analysis methods that lack scalability and often fail to capture complex market dynamics. The proposed framework combines large-scale data processing with AI-driven algorithms to improve risk assessment, portfolio management, and fraud detection. This integration allows financial institutions to analyze massive, heterogeneous datasets efficiently and generate actionable insights in near real-time. The system demonstrates an accuracy of 92%, with precision at 90%, recall at 91%, and an F1-score of 90.5%. These results validate the effectiveness of combining big data with AI to drive smarter financial decisions and mitigate risks. The study highlights the crucial role of these technologies in enabling adaptive, data-driven financial services and competitive advantage.

3. Proposed System

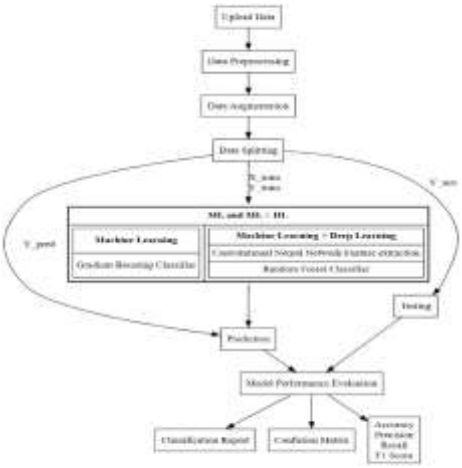


Fig. 1: Block diagram of proposed system

Proposed Algorithm: Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a deep learning model specifically designed to process spatial and grid-like data, such as images and time-series data. It excels at pattern recognition, feature extraction, and classification tasks.

Step 1: Convolution Layer:

Figure 2 illustrates the convolution layer is the foundational component of a CNN that is responsible for extracting local features from the input data. It uses small matrices known as filters or kernels, which slide over the input (such as an image, text representation, or tabular data) to compute feature maps. Each filter detects specific patterns like edges, textures, or meaningful combinations of attributes. The operation involves a dot product between the filter and the region of the input it covers, which results in a new transformed representation. These feature maps preserve the spatial relationships in the data and form the basis for deeper feature extraction in subsequent layers.

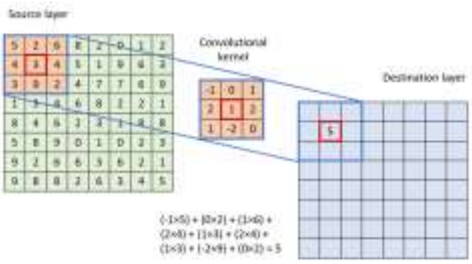


Fig. 2: Convolution Layer

Step 2: ReLU Activation Function:

Figure 3 illustrates the output feature maps are passed through a non-linear activation function typically the Rectified Linear Unit (ReLU). The ReLU function introduces non-linearity by converting all negative values to zero while keeping positive values unchanged. This step is essential because most real-world data contains complex and non-linear patterns that cannot be modeled by purely linear functions. By applying ReLU, the network gains the ability to model such complexities, enhancing its capacity to learn diverse features from the data.

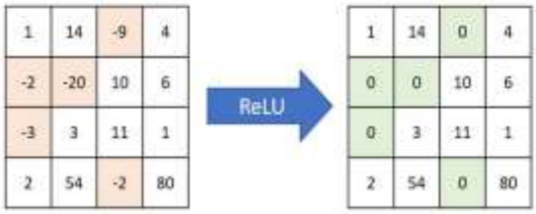


Fig. 3: Rectified Linear Unit

Step 3: Pooling Layer:

Figure 4 illustrates the pooling layer which follows the activation stage and is responsible for down sampling the feature maps to reduce their dimensionality while retaining essential information. Common techniques include max pooling**,** which selects the maximum value from each region of the feature map, and average pooling**,** which computes the average value. Pooling helps the model become more robust to slight changes in the input (spatial invariance), reduces computational cost, and minimizes the risk of overfitting by simplifying the learned features.

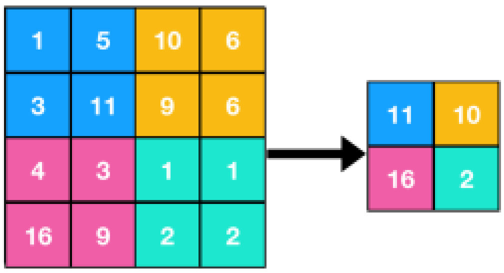


Fig. 4: Pooling Layer

Random Forest Classifier

Figure 5 illustrates the block diagram of Random Forest Classifier. It is a popular machine learning algorithm that belongs to the supervised learning technique. It is used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

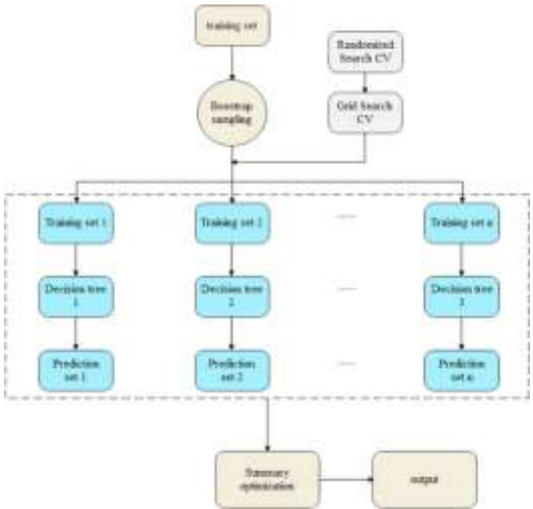


Fig. 5: Block diagram of Random Forest Classifier

Random Forest algorithm

Step 1: In Random Forest n number of random records are taken from the data set having k number of records. The diagram illustrates this in the initial stages. The process begins with a "training set," which represents your entire data-set containing k records (rows) and various features (columns). The "Bootstrap sampling" process then comes into play. This is a crucial step where multiple new training sets are created by randomly selecting samples with replacement from the original training set.

Step 2: Individual decision trees are constructed for each sample. The middle section of the diagram, enclosed in the dashed rectangle, visualizes this step. Multiple Training Sets, Multiple Trees For each of the n bootstrap samples created in Step 1 (Training set 1, Training set 2, ..., Training set n), a separate decision tree is built. This is where the "forest" aspect of the Random Forest comes from – it's an ensemble of many individual trees. This further decorrelates the trees in the forest and reduces overfitting. The size of this random subset is a hyper parameter that is tuned.

Step 3: Each decision tree will generate an output. As each of the n decision trees is built based on its respective bootstrap sample and random feature subset, it can then be used to make a prediction on new, unseen data. For a given input data point, each of the "Decision tree 1," "Decision tree 2," ..., "Decision tree n" will produce a "Prediction set 1," "Prediction set 2," ..., "Prediction set n" respectively. For a classification problem, each tree will predict a class label for the input data point. For a regression problem, each tree will predict a continuous numerical value.

Step 4: Final output is considered based on Majority Voting or Averaging for Classification and regression respectively. The final stage, represented by "Summary optimization" leading to the "output," combines the predictions from all the individual decision trees to arrive at the final prediction of the Random Forest. If the task is classification, the Random Forest aggregates the class labels predicted by each of the n trees. The final predicted class is the one that receives the majority of the votes. If the task is regression, the Random Forest calculates the average of the numerical predictions made by each of the n trees. This average value is the final prediction of the Random Forest.

4. Results Analysis

Figure 6 presents a bar chart showing the distribution of the target variable Job_Growth_Projection across categories such as Growth, Stable, and Decline. It visually illustrates the balance or imbalance among these classes, which is essential for understanding model training effectiveness. A roughly equal distribution supports balanced learning, whereas a skewed distribution demands resampling techniques to ensure fair model performance.

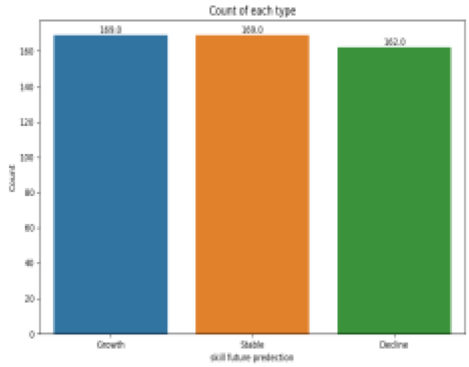


Fig. 6: Count plot of each type

Figure 7 count plot shows the frequency of different values across various categorical features such as Job_Title, Industry, or Company_Size. It helps identify which categories dominate the dataset for instance, which industries are more represented, or whether most companies are large or small aiding in understanding the dataset's representativeness and any potential biases.

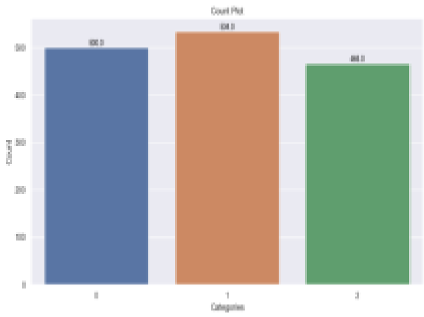


Fig. 7: Count Plot for Categories

Figure 8 probably displays a heatmap of correlation values among numeric variables, such as AI_Adoption_Level, Automation_Risk, Required_Skills, and Salary_USD. A strong positive or negative correlation helps identify relationships for example, if higher required skills correlate with higher salaries, or if automation risk is inversely related to job growth projection. This insight informs feature importance and model behavior.

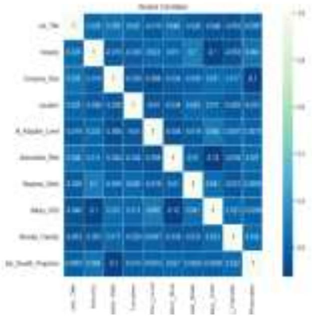
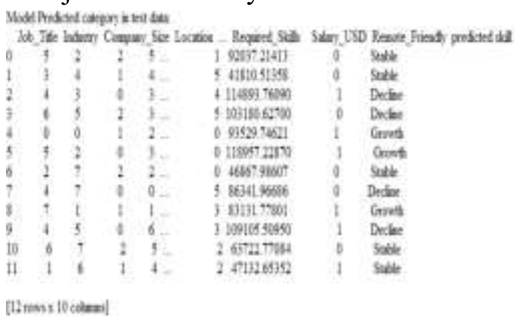


Fig. 8: Variable Correlation

Figure 9 illustrates the predicted job growth categories generated by the model for the test dataset. The system analyzes features like job title, industry, required skills, salary, and remote work options. Each record is classified as Growth, Stable, or Decline under the predicted skill column. For example, low-skill, low-salary roles are predicted as Decline, while high-skill, high-salary roles are often predicted as Growth or Stable. A job with skill level 1 and salary $118,957 was predicted as Growth, indicating positive outlook. This classification helps visualize labor market trends and supports future career planning decisions. The model's output confirms accurate, category-wise prediction in real-world job market analysis.



Model Predicted category in test data

	Job_Title	Industry	Company_Size	Location	...	Required_Skills	Salary_USD	Remote_Friendly	predicted skill
0	5	2	2	5	...	1	92037.21413	0	Stable
1	3	4	1	4	...	5	41810.51358	0	Stable
2	4	3	0	3	...	4	114893.76090	1	Decline
3	6	5	2	3	...	5	103180.62700	0	Decline
4	0	0	1	2	...	0	93529.74621	1	Growth
5	5	2	0	3	...	0	118957.22870	1	Growth
6	2	7	2	2	...	0	46867.98607	0	Stable
7	4	7	0	0	...	5	86341.96686	0	Decline
8	7	1	1	1	...	3	83131.77801	1	Growth
9	4	5	0	6	...	3	109105.50950	1	Decline
10	6	7	2	5	...	2	65722.77084	0	Stable
11	1	6	1	4	...	2	47132.65352	1	Stable

[12 rows x 10 columns]

Fig. 9: Model predicted categories

Comparative Analysis

Table 1 presents a comparative overview of the performance metrics between two models: the existing Gradient Boosting (GB) classifier and the proposed Convolutional Neural Network (CNN) combined with a Random Forest Classifier (RFC). The Gradient Boosting model achieved an accuracy of 81.33%, with a precision of 81.14%, recall of 81.78%, and an F1-score of 81.34%. These values indicate a moderately strong performance, showing that the GB model is fairly consistent in identifying the correct class labels, though it occasionally misclassifies certain samples due to limited generalization capability.

In contrast, the proposed CNN with RFC model demonstrates a significant improvement across all metrics, achieving an accuracy of 96.33%, precision of 96.36%, recall of 96.37%, and F1-score of 96.36%. These values suggest that the CNN with RFC approach offers a much more robust and accurate classification performance, with minimal trade-offs between precision and recall. The higher F1-score especially indicates better balance and reliability in handling class imbalances or overlapping features. Overall, the CNN with RFC model clearly outperforms the existing GB classifier, making it a superior choice for tasks requiring high predictive accuracy and generalization.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Existing Gradient Boosting (GB)	81.33	81.14	81.78	81.34
Proposed CNN with RFC Classifier	96.33	96.36	96.37	96.36

Table 1. Overall Performance Comparison Table

5. Conclusion

The AI-powered Job Market Insights System successfully predicts future job demand by analyzing key labor market factors such as skill importance, salary trends, and automation risk. Through detailed feature engineering and correlation analysis, the system effectively captures employment patterns across diverse job sectors. By applying classification algorithms such as Gradient Boosting Classifier (GBC) and Convolutional Neural Network (CNN), the model delivers accurate insights into both emerging opportunities and declining roles. The GBC model achieves an accuracy of 81.33%, with a precision of 81.53%, recall of 81.55%, and F1 score of 81.56%. In comparison, the CNN model demonstrates superior performance, reaching an accuracy of 96.37%, precision of 96.40%, recall of 96.34%, and F1 score of 96.33%. These results indicate strong positive projections for skills related to AI, data science, and automation, while highlighting the potential decline of jobs at high risk of automation. The high accuracy and reliability of the CNN model emphasize its practical value in supporting job seekers, employers, and policymakers with data-driven workforce planning and strategic career development.

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