IJERST

International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 21 No. 3 (1) 2025

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com
Vol. 21, No. 3(1), 2025

Research Paper

SKILLCAST AI: PREDICTIVE MODEL FOR FORECASTING FUTURE JOB MARKET DEMANDS

A. VeeraBabu, Nandi Satya Siddartha, Vinod I, Vishwa M
Department of Computer Science and Engineering (AIML), Kommuri Pratap Reddy Institute of Technology, Ghatkesar, Medchal, 500088.

Received: 05-6-2025 Accepted: 03-7-2025 Published: 10-7-2025

ABSTRACT
The global job market is undergoing rapid transformation, with over 85% of jobs in 2030 yet to be created, and nearly 40% of the current workforce requiring reskilling within the next five years. Additionally, AI and automation are expected to displace 75 million jobs but create 133 million new ones by 2025, signaling a significant shift in skill demand. Traditional methods are manual, reactive, and rely on outdated labor reports, making them unsuitable for processing real-time job market data. Existing methods of analyzing job market trends, such as the use of Gradient Boosting Classifier (GBC), often result in lower efficiency and accuracy, failing to effectively predict future skill requirements. To address these limitations, this work proposes an AI-powered hybrid deep learning framework to predict whether jobs in particular companies or sectors are in growth, decline, or stable. The system collects and preprocesses large-scale job postings and labor trend data, utilizing techniques such as keyword extraction, text normalization, and feature encoding. Our proposed solution integrates a Convolutional Neural Network (CNN) for deep semantic pattern learning in job descriptions and a Random Forest Classifier (RFC) for robust, interpretable decision-making. This hybrid approach significantly enhances both efficiency and accuracy compared to the Gradient Boosting Classifier, capturing both contextual and statistical patterns in job data. The model provides valuable insights into emerging skill trends, offering foresight into job market shifts to support workforce planning and policy-making.
Key words: Job Market Prediction, Labor Market Analytics, Predictive Analytics, AI in HR Tech, Industry-Specific Skill Mapping

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.

Furthermore, the misalignment between available skillsets and emerging job roles continues to widen. According to LinkedIn's Workplace Learning Report 2024, 89% of learning and development professionals agree that proactively identifying future skill requirements is critical, yet only 26% of organizations feel confident in their ability to do so. This gap indicates a growing demand for data-driven approaches that can analyze vast volumes of labor market data, detect skill trends, and provide

Fig 1. AI in job market

actionable insights. With the ever-expanding availability of online job postings, professional profiles, and skill taxonomies, there is a unique opportunity to harness intelligent systems. AI-powered job market analysis isn't just useful for companies; it changes the game for employees too. Professionals use AI-driven predictions to identify which skills to learn next, ensuring they stay relevant in evolving industries. Platforms like LinkedIn, Coursera, and Udacity already use AI to suggest personalized learning paths for workers who want to upskill. HR teams can also design better training programs, making career transitions smoother and ensuring that employees remain competitive in an AI-driven world. By combining AI insights with workforce planning, businesses and individuals can navigate the future job market with confidence. AI-powered job market insights go beyond just hiring—they reshape workforce strategies by analyzing trends and predicting future demands. Businesses can use AI to optimize recruitment, ensuring they hire candidates with the right skills for evolving industries. AI also helps in talent retention, identifying employees who potentially need upskilling or reskilling to stay competitive. For employees, AI-driven insights provide personalized career recommendations, helping them choose the best learning paths based on industry trends. Platforms like LinkedIn and Coursera already use AI to suggest courses that align with future job opportunities. Governments and policymakers benefit from AI-powered workforce analytics by designing education systems that match job market needs. AI helps in reducing unemployment by ensuring training programs focus on skills that will be in demand. By integrating AI into workforce planning, industries can stay adaptable, ensuring long-term career growth, innovation, and economic stability.

2. LITERATURE SURVEY

This literature survey aims to explore existing research and developments related to the use of AI in predicting future skill demands. It reviews key methodologies, tools, and frameworks employed in analyzing job market trends using machine learning, natural language processing, and big data analytics. Additionally, it highlights the strengths and limitations of current systems and identifies research gaps in forecasting skill requirements across different sectors. By synthesizing insights from previous studies, this survey lays the foundation for developing an AI-powered model capable of generating accurate, real-time predictions about emerging skills, thereby supporting policymakers, educators, and job seekers in making informed decisions in a rapidly changing employment landscape. 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.

3. PROPOSED SYSTEM

The initial step involves uploading raw input data into the system. This data can include job listings, required skills, resumes, company profiles, and market information. These inputs serve as the foundation for the entire pipeline. At this stage, the data is in its unprocessed, original form and often contain inconsistencies, missing values, or irrelevant attributes that need refinement. The uploaded data acts as the raw material upon which subsequent preprocessing, analysis, and predictions are based.

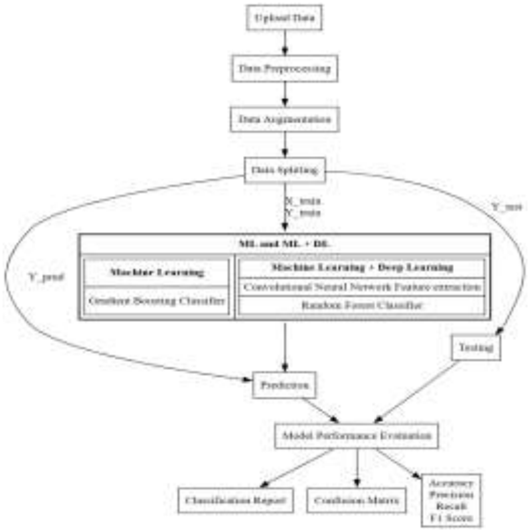

Figure 2. Block diagram of proposed system

In the data preprocessing phase, raw job market data is cleaned, formatted, and structured by addressing missing values, removing duplicates, and standardizing inconsistent formats (e.g., variations in job titles). Categorical features like Job_Title, Industry, Location, and Company_Size are numerically encoded using techniques like Label Encoding, while numerical features are normalized or scaled to ensure uniformity and enhance model performance. To address class imbalance in the job growth categories ('Growth', 'Stable', 'Decline'), data augmentation techniques such as SMOTE or random oversampling are applied to enrich underrepresented classes and prevent model bias. The dataset is then split into training (80%) and testing (20%) sets to ensure unbiased evaluation. Two modeling approaches are employed: a traditional machine learning model using a Gradient Boosting Classifier to capture complex feature interactions, and a hybrid ML + DL approach where a Convolutional Neural Network (CNN) performs feature extraction, and a Random Forest Classifier completes the prediction task. After training, these models predict job growth categories on unseen test data, and their predictions (Y_pred) are compared with actual outcomes (Y_test) to evaluate performance. Key metrics such as accuracy, precision, and recall are computed to assess how well the models generalize and to identify any potential weaknesses, ensuring the system is robust and deployable for real-world job trend forecasting.

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.

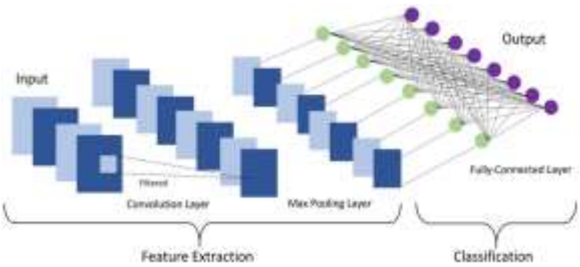

Figure 3. CNN Diagram

CNNs (Convolutional Neural Networks) offer several advantages over Gradient Boosting Classifiers (GBC), particularly when dealing with complex or high-dimensional data. One of the key strengths of CNNs is their ability to automatically learn and extract intricate features from raw input data, eliminating the need for manual feature engineering. This makes them especially effective for unstructured data types such as images, text, or time-series signals. CNNs also tend to achieve higher accuracy in such scenarios due to their deep architecture and hierarchical pattern learning capabilities. Additionally, CNNs are highly scalable and can efficiently handle large datasets with the support of GPU acceleration, enabling faster training and better generalization. Unlike GBC, which often requires extensive preprocessing and feature transformation, CNNs can work directly with raw or minimally processed data, reducing the manual effort and complexity in preparing the input.

Figure 4 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.

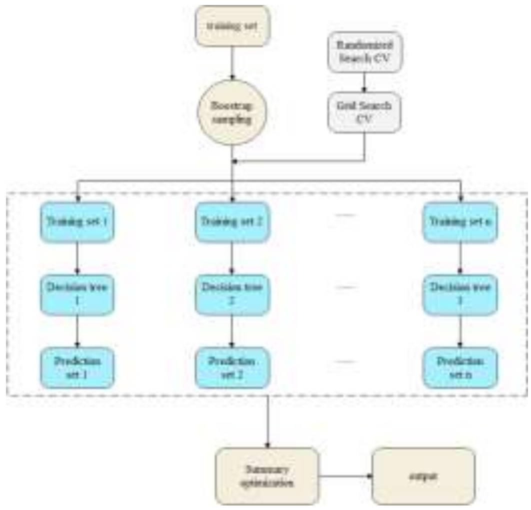

Figure 4. Block diagram of Random Forest Classifier

The Random Forest algorithm begins with Step 1, where a process called bootstrap sampling is used to create multiple new training sets by randomly selecting records with replacement from the original dataset containing *k* records. These bootstrapped datasets introduce diversity, which is critical to building a robust ensemble. In Step 2, a separate decision tree is constructed for each of these *n* bootstrapped samples, each using a random subset of features at every split. This randomness in both data and feature selection helps decorrelate the individual trees and significantly reduces the risk of overfitting. Step 3 involves making predictions using each of these decision trees on new, unseen input data. For classification tasks, each tree outputs a class label, and for regression tasks, a continuous value. In Step 4, the final output of the Random Forest is determined by aggregating the predictions from all individual trees — using majority voting for classification or averaging for regression. The algorithm is characterized by several important features: diversity, since each tree uses different features and data; immunity to the curse of dimensionality, as each tree only considers a subset of features; parallelization, allowing trees to be built independently and efficiently using CPU resources; and stability, as combining the outputs of multiple diverse trees results in more reliable and generalized predictions.

4. RESULTS

Figure 5 represents successful dataset loading and displays the first few rows of the dataset. It includes detailed job information such as Job Title, Industry, Company Size, Location, AI Adoption Level, Automation Risk, Required Skills, Salary_USD, Remote Friendly status, and Job Growth Projection. For example, the first entry is a Cybersecurity Analyst in the Entertainment industry at a Small company with a Growth projection and a salary of $111,392.17, highlighting the structured and rich nature of the data.

Predicting AI_Job_Market_Insights Dataset

	Job_Title	Industry	Company_Size	...	Salary_USD	Remote_Friendly	Job_Growth_Projection
0	Cybersecurity Analyst	Entertainment	Small	...	111392.165243	Yes	Growth
1	Marketing Specialist	Technology	Large	...	93792.562466	No	Decline
2	AI Researcher	Technology	Large	...	107170.263069	Yes	Growth
3	Sales Manager	Retail	Small	...	93027.953758	No	Growth
4	Cybersecurity Analyst	Entertainment	Small	...	87752.922171	Yes	Decline

[5 rows x 10 columns]

Figure 5. Dataset Loaded

Figure 6 presents a countplot 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.

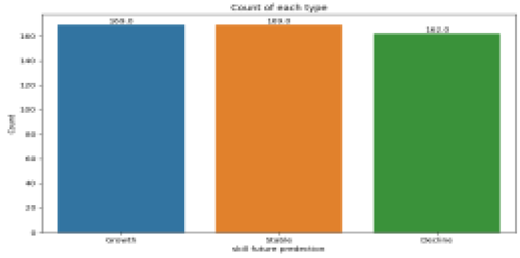

Figure 6. Countplot of each type

Figure 6 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.

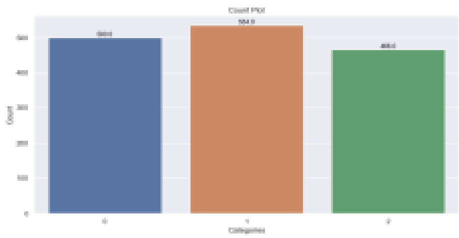

Figure 7. Count Plot For Categories

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.

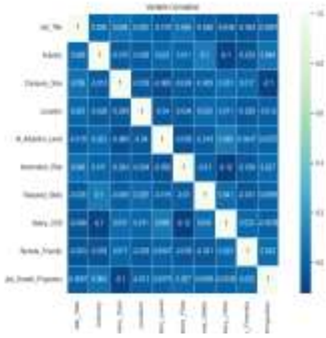

Figure 8. Variable Correlation

Figure 9 highlights the superior performance of the proposed hybrid model combining a Convolutional Neural Network with a Random Forest Classifier (CNN + RFC). It significantly outperforms the GBC with an accuracy of 96.33%, precision of 96.36%, recall of 96.37%, and an F1-score of 96.36%. All three classes—Growth, Stable, and Decline—show very high precision and recall values (above 95%), with the Growth class reaching a recall of 98%. The macro and weighted averages are nearly identical, indicating balanced and reliable performance across all categories.

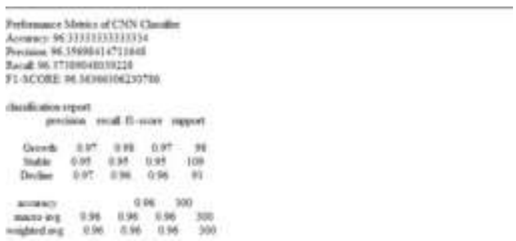

Figure 9. Proposed CNN with RFC Classifier Performance

Figure 10. Model predicted categories

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.

REFERENCES

[1]. Bissadu, Kossi Dodzi, Salleh Sonko, and Gahangir Hossain. "Society 5.0 enabled agriculture: Drivers, enabling technologies, architectures, opportunities, and challenges." Information Processing in Agriculture 12, no. 1 (2025): 112-124.

[2]. Kim, Hyunsu, Kevin Kam Fung So, Seunghun Shin, and Jing Li. "Artificial intelligence in hospitality and tourism: Insights from industry practices, research literature, and expert opinions." Journal of Hospitality & Tourism Research 49, no. 2 (2025): 366-385.

[3]. Ooi, Keng-Boon, Garry Wei-Han Tan, Mostafa Al-Emran, Mohammed A. Al-Sharafi, Alexandru Capatina, Amrita Chakraborty, Yogesh K. Dwivedi et al. "The potential of generative artificial intelligence across disciplines: Perspectives and future directions." Journal of Computer Information Systems 65, no. 1 (2025): 76-107.

[4]. Al-Raeei, Marwan. "The smart future for sustainable development: Artificial intelligence solutions for sustainable urbanization." Sustainable development 33, no. 1 (2025): 508-517.

[5]. Hassan, Dler O., and Bryar A. Hassan. "A comprehensive systematic review of machine learning in the retail industry: classifications, limitations, opportunities, and challenges." Neural Computing and Applications 37, no. 4 (2025): 2035-2070.

[6]. Weichselbraun, Albert, Norman Süsstrunk, Roger Waldvogel, André Glatzl, Adrian MP Braşoveanu, and Arno Scharl. "Anticipating Job Market Demands—A Deep Learning Approach to Determining the Future Readiness of Professional Skills." Future Internet 16, no. 5 (2024): 144.

[7]. Erekath, Swathi, Holger Seidlitz, Monika Schreiner, and Christian Dreyer. "Food for future: Exploring cutting-edge technology and practices in vertical farm." Sustainable Cities and Society (2024): 105357.

[8]. Singh, Bhupinder, and Christian Kaunert. "Future of Digital Marketing: Hyper-Personalized Customer Dynamic Experience with AI-Based Predictive Models." In Revolutionizing the AI-Digital Landscape, pp. 189-203. Productivity Press, 2024.

[9]. Zakhidov, Gafurdjan. "Economic indicators: tools for analyzing market trends and predicting future performance." International Multidisciplinary Journal of Universal Scientific Prospectives 2, no. 3 (2024): 23-29.

[10]. Hossain, Fahim, GM Selim Ahmed, Shree Pritom Paul Shuvo, Abeda Najmin Kona, Mostarifa Umme Hani Raina, and Fisan Shikder. "Unlocking artificial intelligence for strategic market development and business

growth: innovations, opportunities, and future directions." Edelweiss Applied Science and Technology 8, no. 6 (2024): 5825-5846.