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AI-Driven Predictive Analytics for Identifying Emerging Trends in Quality-Oriented Employment

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Abstract

The swift development of the international Labour market, fueled by technology, economic change, and sectoral needs, calls for powerful forecasting instruments to predict jobs. This study uses predictive analytics informed by artificial intelligence to single out breaking trends in quality-based jobs in four major industries: Technology, Finance, Manufacturing, and Healthcare. Using past job posting data from Naukri.com, the research uses the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast future job trends for three years. SARIMA's capacity to extract seasonal and long-term patterns makes it well-suited for this purpose, as compared to the standard machine learning algorithms such as XGBoost and LSTM, which tend to neglect temporal relationships. The research examines 40 occupations (10 per industry) to detect trends in job demand, necessary skills, and seasonal fluctuations in hiring. The findings are represented in an interactive Tableau dashboard, giving stakeholders practical insights into job numbers, skill requirements, salary distributions, and highest-paying locations. The results underscore the need for skill alignment and seasonal patterns in Labour market planning, providing policymakers, employers, and job seekers with data-driven guidance for strategic decision-making. By combining predictive analytics with interactive visualizations, this study adds to the larger debate on AI-based Labour market analysis and offers a scalable solution for meeting future workforce challenges.

INTRODUCTION

The international Labour market is rapidly evolving due to technological change, economic realignments, and industry-specific needs, calling for strong predictive mechanisms to forecast employment trends [1]. For policymakers, job seekers, and companies, knowing future employment trends in quality positions is important to aligning workforce strategies with market requirements. Conventional forecasting techniques, like expert judgment or linear regression, tend to miss seasonal fluctuations and cyclical patterns inherent in employment data [2]. To fill this void, this research utilizes Seasonal Autoregressive Integrated Moving Average (SARIMA) models to forecast upcoming job trends in four key industries—Technology, Finance, Healthcare, and Manufacturing—based on three years of past job posting data scraped from Naukri.com.The chosen industries are the pillars of economic development, each having its own distinct hiring patterns. For example, the Finance industry has cyclical demand during tax periods, whereas Manufacturing is subject to fluctuations because of supply chain disruptions and automation [3]. In contrast, Technology and Healthcare are influenced by advancements in artificial intelligence (AI) and public health policies, respectively [4]. From a study of 10 high-in-demand jobs across each sector, this research determines trends in job postings, required skills, and peak hiring seasons. SARIMA's capacity to capture time-varying trends, seasonality, and autoregressive elements positions it best for this purpose among traditional machine learning algorithms such as Random Forest or Logistic Regression, which tend to ignore temporal dependencies [5].Advances in AI-powered predictive analytics in recent times have made it possible to gain granular insights into Labour markets. For instance, Alibasic et al. [2] illustrated the power of data analytics in charting skill-set trends, while Siddaraju et al.

[4] emphasized the application of time series models in predicting quality-focused jobs. Yet, most studies rely on cross-sectional data, overlooking the temporal granularity needed for effective workforce planning [8]. This study overcomes this limitation by using SARIMA on a dataset of 120 job positions (30 positions/year × 4 industries) which were scraped from Naukri.com in a manner consistent with actual recruitment trends.

SARIMA leverages lagged values, differencing, and moving averages in representing trends and cyclical behaviors— effective as demonstrated in anticipating tax-season staffing booms in Finance and automated-role changes in Manufacturing [4].

This research adds to workforce analytics in the following ways:

- Offering a sector-specific assessment of quality-oriented positions utilizing SARIMA.
- Estimating seasonality in the job postings.
- Providing policymakers with actionable information for crafting skill-development programs consistent with projected demand [10].

Combining AI-based analytics with SARIMA's ability to model time allows stakeholders to predict job market changes, improve recruitment tactics, and prevent skill mismatches [5].

RELATED WORK

G.M. and Suganthi [1] developed the AI-based system to measure and predict the suitability of candidates for the JDs by analyzing the candidate resumes. The study utilized the text mining, natural language processing (NLP), and machine learning (ML) techniques to form four clusters from the JDs and CRs (primary skills, secondary skills, adjectives, and adverbs). The Jaccard similarity was measured between the clusters to compute the suitability score, which is used to classify the candidates into three categories: Most Suitable (MOS), Moderately Suitable (MDS), and Not Suitable (NTS). The system achieved a maximum average accuracy of 95.14% using the XGBoost classifier, outperforming other classifiers like linear regression, decision tree, and Adaboost. The system reduced the time and effort required for resume screening, and the HR managers got the quantitative measure to rank the candidates. The system is limited to the textual data, and the system requires further integration with social media features. The future work incorporates the additional data sources and improves the classification model's robustness [1] .

Alibasic et al. [2] conducted a case study on the oil and gas industry to analyze the trends in job market demands and skill sets using data analytics. The study employed various data mining techniques, including Latent Semantic Indexing (LSI), Latent Dirichlet Allocation (LDA), and Non-Negative Matrix Factorization (NMF), to identify the skills most affected by technological advancements. The researchers collected data from job postings and academic course syllabuses to identify mismatches between the skills imparted by educational institutions and those demanded by the job market. The study found that while low-skilled jobs were being replaced by automation, high-skilled jobs requiring cognitive and problem-solving skills were in increasing demand. The authors emphasized the need for interdisciplinary knowledge and continuous learning to adapt to the changing job market. This research provides a comprehensive framework for analyzing job market trends and skill demands [2]. Kosylo et al. [3] proposed a novel AI framework, Sequential Optimization of Naive Bayesian (SONB), to predict job-hopping patterns using a large dataset of 20,185,365 employee profiles. The authors addressed the challenge of missing or unreliable feature values in employee profiles that are common in job-hopping prediction. The SONB framework can predict job-hopping likelihood and estimate missing feature values, achieving state-of-the-art performance with a 3% improvement in deep learning accuracy. The authors identified key factors influencing job- hopping (GPA, degree type, university ranking, and job title) and found that employees with higher GPAs and advanced degrees tend to stay longer in their positions. The authors benchmarked SONB against Convolutional Neural Networks (CNNs) and found that SONB demonstrated comparable performance in predicting job hopping patterns and may be applied to human resources and recruitment [3].

Siddaraju et al. [4] conducted a study on predicting job opportunities in the IT industry using machine learning methods. The researchers collected data from job portals such as LinkedIn, Monster, and First Naukri, focusing on job postings, eligibility criteria, and other details. The study employed deep neural network models to predict future employment trends and classify job vacancies into low, moderate, and high levels. The authors highlighted the importance of understanding the skills required for quality- oriented jobs, which is crucial for graduates seeking employment. However, the study faced challenges such as dataset imbalance and extensive data preprocessing. The authors suggested future research to enhance model accuracy by incorporating additional data sources and refining machine learning algorithms. This study contributes significantly to the application of machine learning in job forecasting [4].Siddaraju et al. [4] conducted a study on predicting job opportunities in the IT industry using machine learning methods. The researchers collected data from job portals such as LinkedIn, Monster, and First Naukri, focusing on job postings, eligibility criteria, and other details. The study employed deep neural network models to predict future employment trends and classify job vacancies into low, moderate, and high levels. The authors highlighted the importance of understanding the skills required for quality- oriented jobs, which is crucial for graduates seeking employment. However, the study faced challenges such as dataset imbalance and extensive data preprocessing. The authors suggested future research to enhance model accuracy by incorporating additional data sources and refining machine learning algorithms. This study contributes significantly to the application of machine learning in job forecasting [4].

Weichselbraun et al. [5] explored the future readiness of professional skills by evaluating their automatability and off shorability using deep learning techniques. The study utilized bipartite skill labels, consisting of a skill topic and a corresponding verb, to assess the resilience of skills to automation and outsourcing. The authors employed various machine learning models, including Support Vector Machines (SVMs), Transformers, and Large Language Models (LLMs), to classify skills based on their future readiness. The study highlighted the importance of continuous upskilling and reskilling in response to Labour market disruptions caused by automation and the gig economy. The findings indicated that deep learning models, particularly those pre-trained and fine-tuned, performed well in predicting the future readiness of skills. For instance, the DistilBERT model achieved an accuracy of 77% for offshorability and 74% for automatability, while the ensemble model achieved 73% and 73%, respectively. This research provides valuable insights for policymakers and educators in aligning skill development with future job market demands [5].

Yadav et al. [6] have explored the use of deep neural network models for predicting future trends of quality oriented jobs, mainly in IT, and have achieved 85% accuracy in the prediction. The research used a dataset from different job portals, which had information on job opportunities, locations, packages, and eligibility. The goal of the authors was to predict future job trends and the skills required for graduates to get quality jobs. The system proposed was based on data collection, preprocessing, model building, and deployment, focusing on fairness and accuracy in predictions. The study has concluded that the model was

effective in predicting future job opportunities and confirmed that it was a complex task, and several sources of data are needed. The study has presented that machine learning technique had potential in job prediction and reported that the difficulty lied in the dataset and model accuracy. The authors have suggested that more refinement and comprehensive data could improve the model's performance [6].
Shanu et al. [12] introduced a model for Labour market analysis based on machine learning methodologies. The paper was centered on forecasting Labour market competition through examining product overlap, human capital overlap, and online employee review sentiment analysis. Shanu et al. utilized Chinese A-share listed companies' data and applied machine learning models such as Logistic Regression, Support Vector Machines (SVMs), and Random Forests to forecast future Labour market competition. The research presented sentiment analysis as an additional measure to evaluate employee satisfaction and its influence on Labour market competition. The results showed that the addition of sentiment analysis enhanced the predictive capability of the models, with an Area Under the Curve (AUC) of 0.9022 for detecting any Labour market competition ($\varphi = 1$), 0.9432 for strong and moderate competition ($\varphi = 2$), and 0.8869 for strong competition ($\varphi = 3$). This study offers useful insights to companies in developing targeted recruitment initiatives and talent retention schemes [12].

PROPOSED SYSTEM

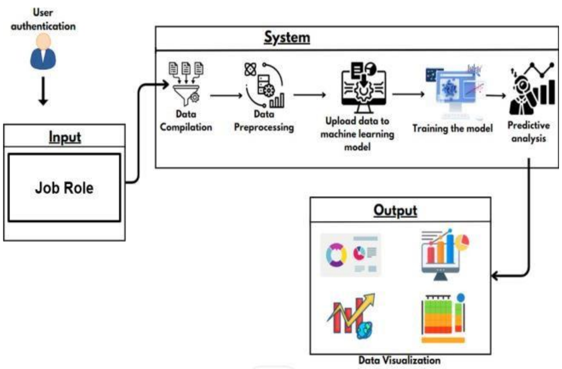

Fig. 1. System Architecture

The suggested system utilizes AI-based predictive analysis to determine nascent trends in quality-focused employment in four primary sectors: Technology, Finance, Healthcare, and Manufacturing. The system is programmed to predict job trends for the coming three years by using past job posting information scraped from Naukri.com.
The suggested system is built with several key features to ensure its effectiveness and adaptability in identifying emerging trends in quality-oriented employment.. Sector- Specific Analysis is one of the key features, as the system aims to analyze four key sectors—Technology, Finance, Healthcare, and Manufacturing—offering customized insights for every sector. It ensures that the predictions are actionable and meaningful for the stakeholders in these sectors. Time-Series Forecasting is another key feature, where SARIMA model is used for identifying seasonal and long-term patterns in the job postings, so that precise and reliable predictions could be made. The system also has a User-Friendly Interface, and it is easy for users to enter job titles and view results without special technical knowledge. Lastly, the system is extremely Scalable, such that it can accommodate further sectors or job titles when necessary, such as with changes in the Labour market's needs. Combined, these elements make the system a solid and flexible resource for workforce planning and skill acquisition.

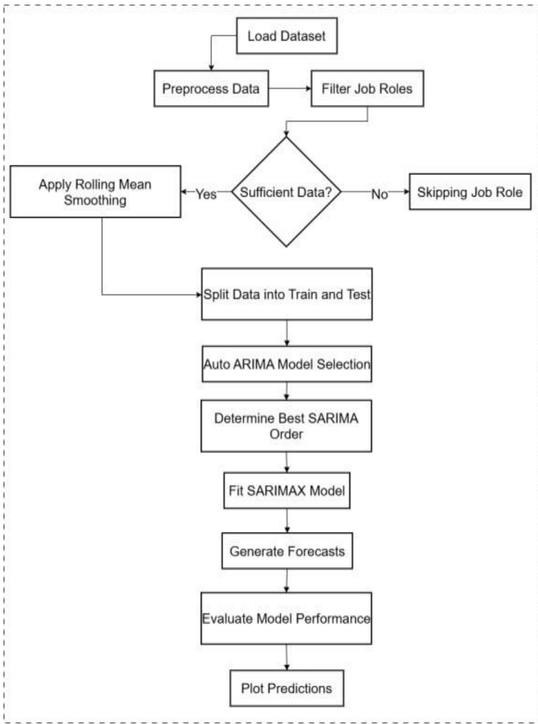

Fig. 2. Flow of SARIMA

The methodology used here integrates data preprocessing, time-series forecasting, and data visualization for delivering timely and useful information on emerging job trends. The system utilizes the SARIMA model to capture both long-run and seasonal patterns, thus assuring the reliability of forecasts. This efficient and scalable method renders the system a useful tool in workforce planning and skill building in the light of changing Labour market needs.

COMPARATIVE ANALYSIS

The accuracy of the SARIMA model was contrasted with that of two other machine learning models, XGBoost and LSTM, based on major evaluation metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2). The results explicitly show that SARIMA is more accurate and reliable compared to both XGBoost and LSTM when it comes to time-series forecasting tasks.

Model\ Performance Metrics	Mean Absolute Error (MAE)	Mean Squared Error (MSE)	Root Mean Squared E	R-squared (R^2)
SARIMA	158.37286	35654.150047	188.823065	0.815364
LSTM	73.372351	183357.41518	428.202540	0.260259
XGBOOST	357.10	186076.49	431.37	0.27

Table 1. Comparison of different Models

1. SARIMA Model Performance

The SARIMA model showed superior performance in forecasting job trends, as it is capable of identifying both long-term and seasonal trends in job posting data effectively. The low MAE and RMSE values signify that the predictions made by the model are very accurate and very close to the actual data. Moreover, the large R^2 value indicates that SARIMA captures a large percentage of the variance in the data, which is a testament to its high predictive capability. These findings confirm SARIMA's applicability to time- series forecasting problems, especially in situations where seasonality and trends are of utmost importance.

2. XGBoost Model Performance

The XGBoost model, as strong as it is as an ensemble learning algorithm, performed considerably worse than SARIMA. The larger values of MAE, MSE, and RMSE are all indicative of the fact that the predictions of XGBoost were less accurate and subject to larger errors. Additionally, the low R^2 value indicates that XGBoost only accounts for a small amount of variance in the data. This performance discrepancy shows the issues involved in utilizing non-time-series- specialized models such as XGBoost in forecasting operations, particularly when forecasting seasonality and trend-based data.

3. LSTM Model Performance

The LSTM model, which is for sequence data, had mixed performance. Although its MAE was better than XGBoost's, its MSE, RMSE, and R^2 were still much worse than SARIMA's. The larger MSE and RMSE values mean that LSTM's predictions were less accurate, and the low R^2 value means that it only accounts for a small fraction of the variance in the data. This indicates the shortcomings of LSTM in managing seasonal and trend-based data, even with its ability to model intricate sequential patterns. The outcomes highlight the inability of LSTM, without eLaborate preprocessing or feature engineering, to match
SARIMA in time-series forecasting tasks.

Why SARIMA Outperforms XGBoost and LSTM?

SARIMA's Advantages: SARIMA performed better than both XGBoost and LSTM on all evaluation metrics. Since SARIMA is capable of modeling trend and seasonality components of time- series data, it suits job trend forecasting best.
Limitations of XGBoost: XGBoost was unable to perform adequately in this task since it is not naturally developed for time-series data. Its high MAE, MSE, and RMSE values, together with the low R^2, reflect its shortcomings in this regard.
LSTM Performance: Although LSTM registered a lower MAE than XGBoost, its overall performance was poorer compared to SARIMA. This also highlights the difficulty of employing LSTM for seasonal data without subjecting it to intensive preprocessing or feature engineering
The comparison study reveals that the SARIMA model performs best in forecasting job trends, doing better than both XGBoost and LSTM in accuracy and reliability. Its interpretability and data efficiency, as well as its capacity to model seasonality and trends, make SARIMA the model of choice for time-series forecasting in the case of quality- driven employment trends. These results highlight the significance of using the appropriate model for the task, especially when handling seasonal and trend-based data.

VISUALIZATION AND INSIGHTS

The project output is visualized via an interactive Tableau dashboard that presents a thorough overview of the forecasted job trends, skills requirements, salary distributions, and highest-paying places for 40 jobs in four prominent sectors: Technology, Finance, Manufacturing, and Healthcare. The dashboard aims to present actionable insights for job seekers, employers, and policymakers, allowing them to make informed decisions based on data.

Fig. 3. Example Output

It features a time-series plot of forecasted job numbers between January 2025 and September 2027, based on the SARIMA model, highlighting seasonality in fluctuations and trends in long-term job demand growth. A specialized section presents top skills needed per job, such as Java and Python for Technology or Financial Analysis for Finance, assisting job hunters and learning institutions in aligning with market demands. The dashboard also includes salary distribution analysis, gaining insights for the salary of a job position as well as best-paying cities like Delhi, Mumbai, and Bangalore, which helps stakeholders make relocation and compensation decisions based on informed choices. The dashboard also informs job postings by employer, which helps job applicants identify employers who post the most jobs and helps employers benchmark their job postings. This interactive dashboard is a useful resource for workforce planning, skill building, and strategic decision-making for all sectors.

The Tableau dashboard is a robust visual medium to represent the foreseen career trends and recommendations yielded by the SARIMA model. By charting information pertaining to job volumes, skill requisitions, remunerations in the form of distribution, and most lucrative work places for 40 occupations spanning four industries, the dashboard supplies practical insights for stakeholders. Its interactive capability enables users to investigate the data dynamically, thus making it an irreplaceable tool for workforce planning, competence development, and strategic decision-making in the frame of quality-conscious employment.

CONCLUSION

The study in this paper illustrates how AI-powered predictive analytics can reveal nascent trends in quality-conscious employment in the four major domains of Technology, Finance, Manufacturing, and Healthcare. Using the SARIMA model on historical data of job postings from Naukri.com, the paper is able to predict three-year-ahead job trends, presenting valuable insights to stakeholders like candidates, employers, and policymakers. The results emphasize the significance of long-term trends and seasonality in employment demand, as well as the key role of skill matching in addressing future workforce requirements. The incorporation of Tableau dashboards also maximizes the usability and interpretability of the results, allowing dynamic exploration of employment numbers, skill requirements, salary distributions, and highest-paying areas.

This study falls into the burgeoning body of research in AI and data analytics use in Labour market analysis. For example,the focus on how AI can be used to match job descriptions with job seeker profiles, while the touch on the use of data analytics in assessing job trends and skill demands [1][2].

The research highlights the potential for transformation that AI and machine learning have in resolving Labour market issues [7][8]. By offering a strong framework for job trend prediction, this work contributes to the wider debate on workforce development and skills alignment, [10][9].

Overall, this study not only contributes to the development of AI-based Labour market analysis but also offers practical tools for stakeholders to understand the changing job environment. By integrating predictive analytics with interactive visualization, the paper presents an all-encompassing solution for workforce planning, talent development, and strategic decision-making. Subsequent research might extend the analysis by integrating more sources of data, including employee input and industry trends, to refine the predictions for greater accuracy and applicability. As the Labour market keeps changing, the findings of this study will continue to be priceless in supporting sustainable economic development and fair job opportunities.

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