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A Machine Learning-Based Job Forecasting And Trend Analysis System To Predict Future Job Markets Using Historical Data

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***Abstract*— Over the last two decades, technological advancements have created more job markets and job opportunities than ever. With the ever-increasing demand, it has become vital for academic institutions and businesses to keep up with employment requirements. The problem is more severe for modern and rapidly evolving industries such as software development. This study implements a prediction system for job trends to enable job seekers, organizations, and academic institutions to understand and align their endeavors to match the market requirement. Employers can benefit from the system by using it to identify potential talent shortages and proactively address them. Policymakers can also use the system to understand the potential impacts of changes in the job market on the economy, enabling them to make informed decisions about supporting employment growth.**

The prediction is made possible by creating a rich dataset based on more than 522,180 job listings from the past 24 months in the software industry. The dataset is fed to a Bidirectional LSTM model to predict the future trends of the job market for various roles and technologies. Auto-aggressive prediction is implemented using the bi-directional LSTM model as this combination proves to produce the most accurate results after multiple quantitative analyses and evaluations. This study evaluated the proposed solution against known real-world data and it was concluded that the system can predict the job trend for at least the next 12 months with a relatively high accuracy of 95.71%.

Keywords*— *Bi-directional LSTM, Deep Learning, Job Market, Trend, Software Industry, Auto-aggressive prediction

I. Introduction

The study of job market trends is a valuable area of research for several reasons. Understanding the trends in the job market can help individuals make informed career decisions by identifying which industries and occupations are growing or declining. It can also provide valuable insights for businesses, allowing them to make strategic decisions about which products or services to offer and how to allocate resources.

Moreover, the job market is an essential aspect of the economy and is constantly evolving in response to various trends and changes in demand for certain skill sets. Research has shown that some factors can impact the job market, including technological advancements, shifts in consumer behaviour, and economic conditions [6].

One emerging trend in the job market is the increasing demand for digital skills and the rise of the gig economy [8]. As more businesses move online and adapt to hybrid work models, there is a growing need for professionals with expertise in areas such as data analytics and cloud computing [7]. Additionally, the gig economy, which is characterized by freelance and temporary work arrangements, has become more prevalent in recent years, with an estimated 57 million Americans participating in gig work in 2020 [7].

Another trend in the job market is the increasing focus on diversity and inclusion in the workplace [10]. Companies are recognizing the benefits of a diverse workforce and are taking steps to increase representation and foster inclusivity in their hiring and promotion practices. This trend is not only driven by a sense of social responsibility, but also by the realization that diverse teams can lead to improved decision-making and innovation [14].

Understanding the current state and future trends of the job market is crucial for both individuals looking to enter the workforce and organizations seeking to hire the right talent. According to "9 trends that will shape work in 2021 and beyond", the job market will continue to be shaped by several trends in the coming years, including the increasing importance of digital skills, the rise of remote work, and the growing demand for flexible and adaptable workers. Also, they predicted that there will be a greater focus on upskilling and reskilling shortly, as organizations strive to keep their employees current with the changing needs of the market [15].

Other sources, such as "Big data application in job trend analysis" have also emphasized the growing importance of data analytics in the job market [14]. Data science and big data are expected to be in high demand in the coming years, with industries across the board seeking professionals with these skills [7].

In addition to these trends, the COVID-19 pandemic has had a significant impact on the job market, with many industries facing layoffs and hiring freezes. However, some industries have seen an increase in demand for their products and services, such as healthcare and e-commerce [29]. As the world looks to recover from the pandemic, it will be important to keep an eye on these trends and how they may continue to shape the job market in the future.

Also, the job market has a significant impact on individuals' quality of life. Unemployment can lead to financial stress and social isolation while having a good job can provide a sense of purpose and financial stability [16]. The importance of staying current with Information Technology (IT) job trends cannot be overstated. In a rapidly evolving industry, professionals must stay up to date on the latest technologies and trends to remain competitive and relevant in the job market. Also, this is particularly true given the increasing demand for certain skills and job titles as new technologies emerge and industries adapt to the changing landscape [18]. Conducting a job trend analysis can help IT professionals understand the current state of the job market, identify areas of growth and decline, and anticipate future employment demands [17].

In conclusion, understanding IT job trends is essential for professionals in the field to stay current and competitive in a rapidly evolving industry. Conducting a job trend analysis can help IT professionals anticipate future employment demands and identify areas of growth and decline, as well as stay informed about broader trends such as remote work and the importance of continuous learning. By staying informed and adapting to new technologies and approaches, IT professionals can position themselves for success in the constantly changing world of technology.

II. Background And Related Work

A. *Previous Work and Systems for Job Trend & Forecasting Domain*

The below sections illustrate the previous research work and commercial products that are available for the job trend and forecasting domain.

1) *Previous Research Work*

Table I illustrates the previous research works that are available for the job trend and forecasting domain.

TABLE I. PREVIOUS RESEARCH WORK

Previous Work	**Based on Web Scraping and Sentiment Analysis [19].**
Description	Forecast of job availability based on sentiment analysis of job postings.
Approach	Web scraping, sentiment analysis, machine learning
Accuracy	Not mentioned
Pros & Cons	Pros: Can provide real-time forecasts based on current job postings Cons: Limited to job postings available online, may require advanced technical skills for web scraping and sentiment analysis
Previous Work	**In Search of a Job: Forecasting Employment Growth Using Google Trends [4].**
Description	Forecast of employment growth based on Google search data
Approach	Google Trends, machine learning
Accuracy	Not mentioned
Pros & Cons	Pros: Large and diverse dataset from Google search data Cons: May be limited by the quality and accuracy of the search data, may require advanced technical skills for machine learning
Previous Work	**A Job Forecast System Based on Social Media Data and Sentiment Analysis [1].**
Description	Forecast of job availability based on sentiment analysis of social media data
Approach	Social media data, sentiment analysis, machine learning
Accuracy	Not mentioned
Pros & Cons	Pros: Can provide real-time forecasts based on current social media data Cons: Limited to social media data available, may require advanced technical skills for sentiment analysis and machine learning
Previous Work	**Runtime Prediction of Big Data Jobs: Performance Comparison of Machine Learning Algorithms and Analytical Models [2].**
Description	Prediction of runtime for big data jobs using machine learning and analytical model
Approach	Machine learning, analytical models, performance evaluation
Accuracy	Evaluated using performance metrics such as mean absolute error but accuracy not mentioned.
Pros & Cons	Pros: Can provide accurate predictions of runtime Cons: May require advanced technical skills for machine learning and analytical modelling, may be limited to specific types of big data jobs

2) *Existing Systems*

Table II illustrates the similar systems that are available for the job trend and forecasting domain.

TABLE II. EXISTING SYSTEMS

Previous Work	**Bureau of Labor Statistics [9].**
Description	A US government agency that provides data on employment and wages, including projections of future job growth. Produces a variety of reports and publications on the labor market, including the Occupational Outlook Handbook and the Employment Projections program.
Feature	Evaluated using performance metrics such as mean absolute error but accuracy not mentioned.

Pros & Cons	Pros: Trusted and reliable sources of information on the labour market. Data is based on a comprehensive survey of employers and is widely used by researchers, policymakers, and job seekers. Cons: Data is specific to the US labour market and may not be directly applicable to other countries. Projections are based on current trends and may not take into account potential disruptions or shifts in the labor market. Used features: A variety of data sources, including surveys of employers, government agencies, and other organizations.
Previous Work	**World Economic Forum [18].**
Description	An international organization that focuses on issues related to the global economy, including the future of work. Has published a number of reports on the future of jobs and the skills that will be in demand in the coming years, including "The Future of Jobs Report 2020."
Feature	Surveys of employers and expert opinions.
Pros & Cons	Pros: Reports are based on input from a wide range of sources, including employers, industry experts, and government agencies, and provide a global perspective on the future of work. Cons: Reports are based on expert opinions and may not always align with actual trends in the labour market. The focus is on the global economy, and reports may not always be relevant to specific countries or regions.
Previous Work	**LinkedIn's Workforce Report [28].**
Description	A monthly report on job demand and skills in the US and Canada.
Feature	Real-time data, industry and occupation data, regional data, skills data, insights and analysis.
Pros & Cons	Pros: Based on data from a large and diverse group of professionals and provides real-time insights on the job market. Cons: Specific to the US and Canadian job markets and may not be applicable to other countries. Used features: Data from LinkedIn, including job postings and job seeker activity on the site.

According to previous research, several gaps need to be addressed to provide a more comprehensive understanding of the job market. These gaps include:

- A lack of real-time data, with some studies relying on historical data that may not be relevant to current market conditions.
- Limited scope, with many studies focusing on specific industries or occupations rather than the job market as a whole.
- Dependence on advanced technical skills, can make some studies less accessible to researchers and practitioners without these skills.
- A lack of evaluation of accuracy, with some studies failing to provide information on the reliability of their findings.
- Limited data sources, with some studies relying on a single data source such as job postings or Google search data, may not provide a comprehensive view of the job market.
- A lack of integration of multiple data sources could provide a more comprehensive view of the job market if combined.
- A lack of consideration of qualitative factors, such as employer preferences or employee skills, can also impact job demand and supply.

Overall, there is a need for more research that addresses these gaps to provide a better understanding of the job market and its dynamics. Therefore, this project aims to address the gap in understanding of job market trends in the IT field, specifically focusing on roles and skills factors. To achieve this, the following strategies will be employed:

- Collecting job advertisement data.
- Identifying key job market factors.
- Using forecasting methods, including time series analysis.

B. Data Collection

There are many approaches used to collect the data. But below are frequently used ones compared with previous work as the data set is not publicly available [5].

- Web scraping
- Manually collecting data
- Government sources

Table III critically evaluates the identified collection methods.

TABLE III. COMPARISON OF JOB PREDICTION ALGORITHMS

Method	**Web scraping**
Pros & Cons	Pros: Quick and cost-effective method for collecting large amounts of data Cons: May not always be feasible or ethical, depending on the website and the data being collected
Previous work	"Sentimental Analysis on Web Scraping Using Machine Learning Method" used web scraping to gather data for sentimental analysis on job advertisements from online platforms [19]. "Use of Artificial Intelligence and Web Scraping Methods to Retrieve Information from The World Wide Web" also used web scraping to retrieve information from the World Wide Web [20].
Method	**Manually collecting data**
Pros & Cons	Pros: Allows for a more targeted and controlled data collection process Cons: More time-consuming than other methods
Previous work	"Analysis of manual data collection in maintenance context" manually collected data on job advertisements from online platforms [29].

Method	Government sources
Pros & Cons	Pros: Provides valuable information on the overall state of the job market Cons: May not be as detailed or up-to-date as data from online job advertisement platforms
Previous work	"Machine learning algorithms for social media analysis: A survey" used government data and machine learning techniques to predict firms' vulnerability to economic crisis [21].

In conclusion, web crawling will be used as the data collection method for this study. As the data will be collected from public websites, there are no ethical or legal concerns with using web crawling. This method offers the advantages of being quick and cost-effective for collecting large amounts of data. Other methods, such as manually collecting data and using government sources, may be more targeted and controlled, but they are also more time-consuming. Previous research has successfully used web crawling for sentimental analysis on job advertisements and to retrieve information from the World Wide Web, as well as using manually collected data and government data with machine learning techniques to predict firms' vulnerability to the economic crisis.

C. Aspect Extraction Approches

To gain a better understanding of the job market, it is crucial to identify key aspects of job advertisements. There are various techniques for extracting these aspects, each with its own advantages and disadvantages [22].

TF-IDF is often used for aspect extraction because it is effective at identifying important keywords within a given dataset and is easy to implement. By using TF-IDF to analyze job advertisements, trends and changes in the job market can be identified and understanding of the business can be improved. In this study, TF-IDF was selected for aspect extraction due to its effectiveness and practicality. While this is not the main focus of the research, it is still important to identify relevant aspects of job advertisements to gain a deeper understanding of the job market. While other methods for aspect extraction may have their own benefits and drawbacks, TF-IDF has been shown to be effective in various contexts, including the analysis of literary texts and symbolic sequences [30].

D. Job Market Trend Prediction Algorithms

Predicting future trends in the job market is a crucial task that can be assisted by predictive analytics. These algorithms use a set of independent variables to predict a target trend, which is similar to using a regression model with multiple variables. There are several algorithms that have been used in past studies to predict job market trends, and this article will discuss some of the most commonly used models, as well as their applications and theoretical foundations.

When selecting an algorithm for time series prediction, it is essential to consider the nature of the data and the prediction problem. According to the article J. Korstanje, "How to select a model for your time series prediction task [guide]" , it is crucial to understand the characteristics of the data, such as whether it is stationary or non-stationary, and whether it exhibits any seasonal patterns. The article also recommends considering the length of the time horizon for the prediction, as well as the desired level of accuracy and the available computational resources [31].

Some of the algorithms that may be effective for time series prediction tasks, as mentioned in the article, include ARIMA, LSTM, GRU, SARIMA, Prophet and DeepAR. Each of these algorithms has its own strengths and limitations, and the appropriate choice will depend on the specific characteristics of the data and the prediction problem this article will discuss the above most frequently used models, their applications, and their theoretical foundations.

TABLE IV. COMPARISON OF PREDICTION ALGORITHMS

Algorithm	Long Short-Term Memory (LSTM)
Pros & Cons	Pros: Can handle long-term dependencies and complex patterns Cons: Can be computationally intensive
Description	A type of recurrent neural network that is well-suited for handling long-term dependencies and is effective for time series prediction tasks with complex patterns
Previous work	In a number of research papers, the use of Long Short-Term Memory (LSTM) networks for time series prediction has been explored. For example, in "Multivariate Time Series Prediction of Pediatric ICU data using Deep Learning", the authors found that the LSTM model outperformed a Recurrent Neural Network (RNN) model in a pediatric intensive care unit setting [13]. A novel multi-module approach to predict crime based on multivariate spatiotemporal data using attention and sequential fusion model" presents a model for predicting crime that combines multiple models using the fusion technique and utilizes transfer learning to reduce training time [11]. "Stock price prediction based on LSTM deep learning model" found that the use of LSTM networks for forecasting stock prices resulted in better accuracy and robustness compared to traditional statistical models and other machine learning models [23]. "A LSTM neural network approach using vibration signals for classifying faults in a gearbox" also discusses the use of LSTM networks for forecasting rolling bearing vibration signals [24]. In addition, "Investigating the combination of Deep Learning for channel estimation and power optimization in a non-Orthogonal Multiple Access system", presents a survey of deep learning techniques for non-orthogonal multiple access in wireless communication systems [25].
Algorithm	**Autoregressive Integrated Moving Average (ARIMA)**
Pros & Cons	Pros: Works well for stationary data Cons: Requires manually specifying the model parameters
Description	A traditional time series prediction method that works well for stationary data and can be used for both short-term and long-term predictions
Previous work	In "Time series forecasting using ARIMA model A case study of mining face drilling rig",the use of an ARIMA model for forecasting the total cost of a face drilling rig in the Swedish

	mining industry is discussed. The authors found that the model's forecasting ability varied depending on the values of its parameters (p, d, q), and that better estimation of these parameters is necessary for accurate forecasting. They suggest that artificial intelligence techniques, such as a multi-objective genetic algorithm based on the ARIMA model, could be used to improve parameter estimation and forecasting accuracy [12].
Algorithm	**Gated Recurrent Unit (GRU)**
Pros & Cons	Pros: Can handle long-term dependencies Cons: Can be computationally intensive
Description	A type of recurrent neural network that is similar to LSTM and is effective for handling long-term dependencies in time series data
Previous work	In "State change trend prediction of aircraft pump source system based on GRU network" a GRU neural network is used to predict the state change trend of an aircraft pump source system. The authors compare the performance of the GRU model to other models, such as the ARMA model and traditional BP network, and find that the GRU model has higher prediction accuracy and better engineering application value than these other models [26]. In "Trend-GRU model based time series data prediction in melt transport process"), an improved data prediction model called Trend-GRU is proposed. This model, based on the GRU model, is designed to extract the feature of unstable change in data. The authors conduct experiments using temperature and pressure data collected from a spinning factory and find that the model outperforms the original GRU model in terms of prediction accuracy [27].
Algorithm	**Seasonal Autoregressive Integrated Moving Average (SARIMA)**
Pros & Cons	Pros: Can account for seasonal patterns Cons: Requires manually specifying the model parameters
Description	An extension of the ARIMA model that accounts for seasonal patterns in the data and can be effective for predicting time series data with periodic trends
Previous work	In "Trend analysis and SARIMA forecasting of mean maximum and mean minimum monthly temperature for the state of Kerala, India", the authors propose using the SARIMA method for forecasting temperature in Kerala, India. They use 47 years of temperature data from seven stations and apply several tests to determine the non-stationarity of the data and transform it into a stationary time-series. The authors then develop parsimonious and best-fit SARIMA models for each of the fourteen temperature variables and find that the SARIMA(2,1,1)(1,1,1)12 model is the ideal forecasting model for eight out of the fourteen time-series datasets [28].

According to previous research shown in Table IV, it appears that the Long Short-Term Memory (LSTM) algorithm is better for predicting job trends, as it has demonstrated higher prediction accuracy in comparison to other models such as ARIMA and SARIMA In addition, LSTM has the advantage of being able to effectively explore the relevance of data and deeply study the internal change law of data over time. Furthermore, LSTM has a simpler network structure compared to other models like GRU, which not only guarantees prediction performance but also improves the model's training speed and learning ability when training samples are insufficient. For these reasons, it is reasonable to select LSTM as the algorithm for predicting job trends.

III. System Design

A. High-Level Design

The use of various architectural styles can improve design reuse, partitioning, and the overall effectiveness and efficiency of the system. Figure 1 shows the High-Level Architecture of the system along with the tech stack.

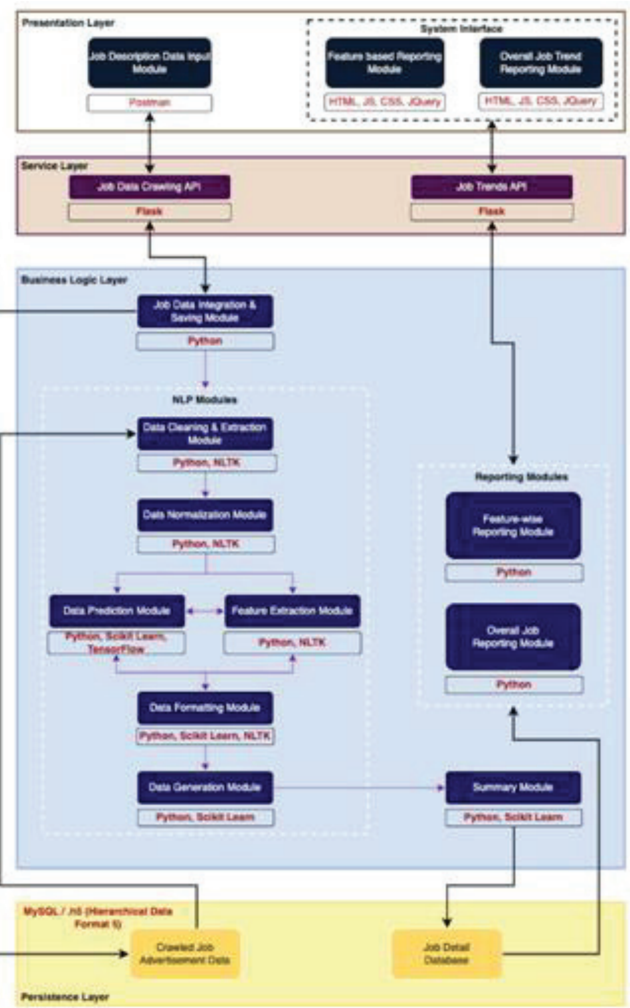

Fig. 1. High-Level Architecture

The consolidation of layered architecture and object-oriented architecture was utilized as architectural styles in the system, to make a more effective and efficient system, as well as to minimize the issues in the project. The project's maintainability is much enhanced by layer separation. For instance, improvements to the user interface only affect the presentation layer, alterations to the programming logic only affect the business logic layer, and modifications to the database or data source only affect the persistence layer.

IV. Development Process

The core functionalities of the system are described in this section along with the pseudocode and algorithms.

A. Data Collection

Data collection is an essential step in any research project, and it is particularly important in a job trend analysis project. In this section, the author describes the methods used to collect data for the project, as well as any considerations or challenges that were encountered during the data collection process. In this proposed solution, the author used two major methods for data collection:

- Crawling job advertisement URLs as a scheduler program.
- Rest API to collect the Job Advertisement URLs from the user.

B. Aspect Identification

As a researcher studying job trends and forecasting future job trends, identifying the key aspects of job advertisements is an important part of the data pre-processing process. By using techniques such as data cleaning, normalization, and feature extraction, it is possible to extract relevant information from job descriptions and use it to analyse trends and make predictions about the job market.

C. Analyse and Calculate the Trend of the Job Advertisements

After identifying an aspect of the Job Advertisement which is related to the IT domain given by the user, the trend is analysed and calculated. Figure 2 illustrates the process used to calculate the trend.

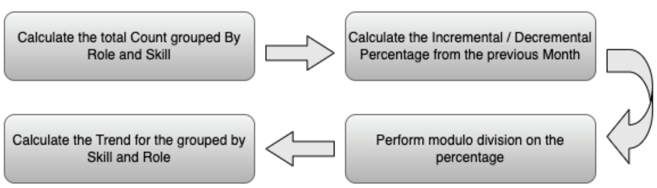

Fig. 2. Process for Trend Calculation

D. Predict the Trend of the Job Market

After calculating the Trend of the crawled Job Description, it is important to accurately predict the trend of the job market. Based on the LR findings, the LSTM algorithm is used to analyze historical job data and identify patterns and trends that can be used to make predictions.

E. Report Summary

Reports are an important tool for communicating and analyzing data and can be used to illustrate the trends and patterns in various aspects such as role and skill in the job market. In the implementation of our job trend and forecasting system, the system used jQuery libraries and Chart API to generate reports that provide users with a convenient way to filter and analyze data.

V. Testing

Both functional and non-functional testing was performed to verify and validate the requirements of the System.

A. Accuracy Testing

Accuracy was analyzed during tasks such as aspect identification and trend analysis with forecasting. Most similar systems used by organizations do not publicly disclose their accuracy results, and many do not use machine learning algorithms such as word embedding or pattern analysis. Therefore, it is not feasible to compare the accuracy of the system to these other systems. However, accuracy was compared using different types of machine learning models, and the bidirectional LSTM model provided the best results, as shown in Figure 3.

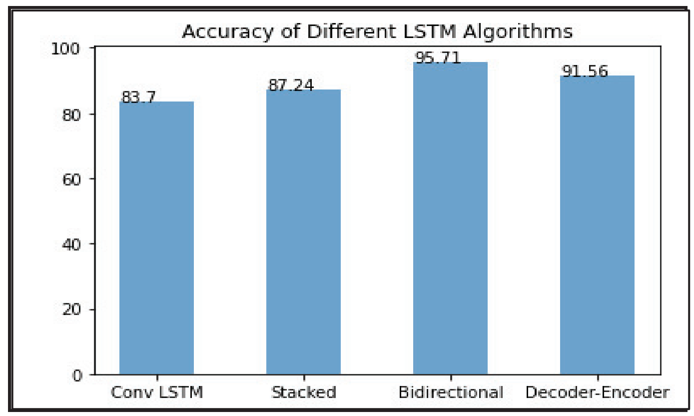

Fig. 3. Accuracy Testing of Different LSTM Algorithms

VI. Conclusion

The proposed solution for predicting and forecasting job trends in the software industry is an innovative approach that has not been attempted before. By compiling a rich dataset through data crawling and using deep learning techniques, this study has advanced the understanding of how to apply machine learning to predict job market trends and has practical implications for researchers and practitioners. The comparison and contrast of multiple deep learning models have also provided a foundation for future research in this area. The release of the dataset on Kaggle will also be valuable for researchers and practitioners interested in studying and predicting job market trends. While the system has some limitations, such as being restricted to the technologies and roles included in the trained data and only supporting the English language, there are opportunities for future enhancements, such as expanding the system to cater to other domains and analyzing job trends in additional factors beyond skills and roles. The author hopes that this solution will be useful for practitioners seeking to make informed decisions about the job market and will inspire further research in this field.

VII. Future Enhancements

The future enhancements of the System are given below:

- Expansion to multiple domains.

- Integration of multiple data
- sources.
- Analysis of additional factors
- Visualization of all job trends.

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References

[1]. S. Yoo, J. Song, and O. Jeong, "Social media contents based sentiment analysis and prediction system," Expert Syst. Appl., vol. 105, pp. 102–111, 2018.

[2]. N. Ahmed, A. L. C. Barczak, M. A. Rashid, and T. Susnjak, "Runtime prediction of big data jobs: performance comparison of machine learning algorithms and analytical models," J. Big Data, vol. 9, no. 1, 2022.

[3]. "Share an online entry "deep learning and non-orthogonal multip," Encyclopedia.pub. [Online]. Available: https://encyclopedia.pub/entry/23934. [Accessed: 15-Jan-2023].

[4]. D. Borup and E. C. M. Schütte, "In search of a job: Forecasting employment growth using Google trends," J. Bus. Econ. Stat., vol. 40, no. 1, pp. 186–200, 2022.

[5]. S. Javaid, "Top 4 data collection methods for machine learning in 2023," AIMultiple, 20-Jun-2022. [Online]. Available: https://research.aimultiple.com/data-collection-methods/. [Accessed: 15-Jan-2023].

[6]. A. Alibasic, H. Upadhyay, M. C. E. Simsekler, T. Kurfess, W. L. Woon, and M. A. Omar, "Evaluation of the trends in jobs and skill-sets using data analytics: a case study," J. Big Data, vol. 9, no. 1, 2022.

[7]. A. AlMosawi et al., "Future job market of information technology in the kingdom of Bahrain," in 2020 International Conference on Innovation and Intelligence for Informatics, Computing and Technologies (3ICT), 2020, pp. 1–6.

[8]. "Job market trends and insights for 2021," Aston Carter Staffing & Recruiting Services. [Online]. Available: https://www.astoncarter.com/en/insights/articles/job-market-trends-and-insights-for-2021. [Accessed: 15-Jan-2023].

[9]. "U.S. bureau of Labor Statistics," Bls.gov. [Online]. Available: https://www.bls.gov/. [Accessed: 15-Jan-2023].

[10]. J. Elliott, "Our look at the top career trends of 2022," Toggl Blog, 05-Jul-2021. [Online]. Available: https://toggl.com/blog/career-trends-2021. [Accessed: 15-Jan-2023].

[11]. N. Tasnim, I. T. Imam, and M. M. A. Hashem, "A novel multi-module approach to predict crime based on multivariate spatio-temporal data using attention and sequential fusion model," IEEE Access, vol. 10, pp. 48009–48030, 2022.

[12]. H. Al-Chalabi, Y. K. Al-Douri, and J. Lundberg, "Time series forecasting using ARIMA model A case study of mining face drilling rig," Diva-portal.org. [Online]. Available: https://www.diva-portal.org/smash/get/diva2:1266336/FULLTEXT01.pdf. [Accessed: 15-Jan-2023].

[13]. F. I. Adiba, S. N. Sharwardy, and M. Z. Rahman, "Multivariate Time Series Prediction of Pediatric ICU data using Deep Learning," in 2021 International Conference on Innovative Trends in Information Technology (ICITIIT), 2021.

[14]. P. Kale and S. Balan, "Big data application in job trend analysis," in 2016 IEEE International Conference on Big Data (Big Data), 2016, pp. 4001–4003.

[15]. B. Kropp, "9 trends that will shape work in 2021 and beyond," Harvard business review, 14-Jan-2021.

[16]. "Job market," Corporate Finance Institute, 31-Mar-2021. [Online]. Available: https://corporatefinanceinstitute.com/resources/economics/job-market. [Accessed: 15-Jan-2023].

[17]. A. Barari, "Here are the 10 Best Jobs to Move Into in 2023," Emeritus Online Courses, 28-Sep-2022. [Online]. Available: https://emeritus.org/blog/top-10-best-jobs-2023/. [Accessed: 15-Jan-2023].

[18]. "The future of jobs report 2020," World Economic Forum. [Online]. Available: https://www.weforum.org/reports/the-future-of-jobs-report-2020/. [Accessed: 15-Jan-2023].

[19]. S. Sahu, K. Divya, N. Rastogi, P. K. Yadav, and Y. Perwej, "Sentimental Analysis on Web Scraping Using Machine Learning Method," Journal of Information and Computational Science, vol. 12, 2022.

[20]. M. Scarnò, "Use of Artificial Intelligence And Web Scraping Methods To Retrieve Information From The World Wide Web," Journal of Engineering Research and Application, vol. 8, 2018.

[21]. Balaji, C. S. R. Annavarapu, and A. Bablani, "Machine learning algorithms for social media analysis: A survey," Comput. Sci. Rev., vol. 40, no. 100395, p. 100395, 2021.

[22]. S. K. Bharti and K. S. Babu, "Automatic keyword extraction for text summarization: A survey," arXiv [cs.CL], 2017.

[23]. Kavinnilaa, Hemalatha, M. S. Jacob, and Dhanalakshmi, "Stock price prediction based on LSTM deep learning model," in 2021 International Conference on System, Computation, Automation and Networking (ICSCAN), 2021, pp. 1–4.

[24]. E. Yang, H. Zhang, X. Guo, Z. Zang, Z. Liu, and Y. Liu, "A multivariate multi-step LSTM forecasting model for tuberculosis incidence with model explanation in Liaoning Province, China," BMC Infect. Dis., vol. 22, no. 1, p. 490, 2022.

[25]. R. Medina et al., "A LSTM neural network approach using vibration signals for classifying faults in a gearbox," in 2019 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC), 2019, pp. 208–214.

[26]. M. Gaballa, M. Abbod, and A. Aldallal, "Investigating the combination of Deep Learning for channel estimation and power optimization in a non-Orthogonal Multiple Access system," Sensors (Basel), vol. 22, no. 10, p. 3666, 2022.

[27]. J. Cui, Y. Cheng, X. Cui, J. Wang, M. Yu, and L. Jiang, "State change trend prediction of aircraft pump source system based on GRU network," in 2020 39th Chinese Control Conference (CCC), 2020, pp. 2457–2460.

[28]. D. Zhao et al., "Trend-GRU model based time series data prediction in melt transport process," in 2019 19th International Conference on Control, Automation and Systems (ICCAS), 2019, pp. 541–546.

[29]. P. Kabbilawsh, D. Sathish Kumar, and N. R. Chithra, "Trend analysis and SARIMA forecasting of mean maximum and mean minimum monthly temperature for the state of Kerala, India," Acta Geophys., vol. 68, no. 4, pp. 1161–1174, 2020.

[30]. S. Wilde, A. Smith, and S. Clark, "Organizations need a dynamic approach to teaching people new skills," Harvard business review, 26-Nov-2021.

[31]. "Workforce insights from LinkedIn's Economic Graph," Linkedin.com. [Online]. Available: https://economicgraph.linkedin.com/workforce-data?trk=workforce&veh=workforce#view-all/by-year. [Accessed: 15-Jan-2023].

[32]. K. Mahlamäki and M. Nieminen, "Analysis of manual data collection in maintenance context," J. Qual. Maint. Eng., vol. 26, no. 1, pp. 104–119, 2019.

[33]. P. Carpena, P. Bernaola-Galván, M. Hackenberg, A. V. Coronado, and J. L. Oliver, "Level statistics of words: finding keywords in literary texts and symbolic sequences," Phys. Rev. E Stat. Nonlin. Soft Matter Phys., vol. 79, no. 3 Pt 2, p. 035102, 2009.

[34]. J. Korstanje, "How to select a model for your time series prediction task [guide]," neptune.ai, 13-Sep-2022. [Online]. Available: https://neptune.ai/blog/select-model-for-time-series-prediction-task. [Accessed: 15-Jan-2023].

[35]. M. Daraghmeh, A. Agarwal, R. Manzano, and M. Zaman, "Time series forecasting using Facebook prophet for cloud resource management," in 2021 IEEE International Conference on Communications Workshops (ICC Workshops), 2021, pp. 1–6.