**DEVELOPING MACHINE LEARNING ALGORITHMS FOR PREDICTING EMPLOYEES' SALARIES IN AN ORGANIZATION: A CASE OF DANGOTE GROUP, NIGERIA**

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**Abstract**  
This research focuses on developing and evaluating machine learning algorithms to predict employee salaries in an organization, using the Dangote Group, Nigeria, as a case study. The primary goal is to create accurate and efficient salary prediction models that can support data-driven compensation decision-making processes. A dataset comprising 1,742 observations and 19 features, including employee demographic, performance, and organizational variables, was analyzed.

The study implemented multiple regression techniques, including Decision Tree Regression (DTR), Elastic Net Regression (ENR), K-Nearest Neighbors (KNN), Linear Regression (OLS), Random Forest Regression (RFR), Support Vector Machine (SVM) Regression, and Gradient Boosting Regression (GBR). The models were evaluated for predictive accuracy, with RFR, DTR, and GBR emerging as the most promising candidates for deployment. However, these models must be carefully tuned to mitigate the risk of overfitting. SVM also presents a viable alternative with competitive performance, while ENR and OLS were found to be less suitable for this dataset.

The research concludes that machine learning models, particularly ensemble techniques, offer significant potential for enhancing salary prediction accuracy. A web application was developed to enable businesses to leverage these models for quick and reliable salary estimations. This study provides valuable insights into applying data science to human resource management, promoting fairness and transparency in compensation systems.

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**CHAPTER ONE**

**1. Introduction**

Accurate wage projection is essential for efficient personnel planning and management in modern organisations. Pay for employees has a big impact on retention, job satisfaction, and organisational productivity. However, traditional salary-setting techniques frequently depend on subjective assessments and ignore dynamic elements like macroeconomic swings, individual performance, and market trends (Smith & Jones, 2022). As a result, businesses are using data-driven methods more and more to improve their decision-making. One of the most effective methods for evaluating intricate datasets and producing accurate predictions is machine learning (ML), a branch of artificial intelligence (AI).

The development of machine learning algorithms to forecast staff pay inside the Dangote Group, one of Nigeria's biggest conglomerates, is the main subject of this study. The study attempts to close the gap between traditional pay estimating methods and cutting-edge computer techniques by utilising historical data. In addition to improving accuracy, this change guarantees compensation management's fairness and openness. In addition to taking into consideration outside variables like market norms and economic situations, the study finds important elements that affect employee salary, including job level, years of experience, educational background, and performance measures.

The suggestion of an intuitive online application to enable real-time wage projection is one of the research's major accomplishments. Businesses can swiftly and efficiently make data-driven choices thanks to the application's integration of predictive insights from machine learning models. As an illustration of the revolutionary potential of AI in human resource management, Google and IBM have used machine learning to forecast staff turnover and optimise pay structures (Brown et al., 2021). In a similar vein, Dangote Group may optimize its wage calculation procedure and match compensation packages with industry standards by implementing ML-based solutions.

This study demonstrates how machine learning may be used practically to address problems in the real world. Businesses such as PayScale, for example, analyse employee wages using machine learning algorithms and give businesses compensation reports that are specific to their sector and region. Organizations have found that these tools are quite helpful in addressing wage discrepancies and increasing employee satisfaction (Payscale, 2023). The Dangote Group's application of these cutting-edge techniques in Nigeria provides insightful information on the particular cultural and financial difficulties associated with labour management in emerging nations.

**1.1 Background**

The process of predicting salary is intricate and multidimensional, impacted by elements including job positions, education, industry standards, and employee experience. In the past, companies have decided on pay structures based on subjective assessments, market research, and benchmarking. But these traditional approaches frequently result in inefficiency, pay inequalities, and employee discontent (Brown, 2020). The limits of conventional methods are addressed by the rise of big data and machine learning (ML), which give businesses advanced capabilities to evaluate enormous datasets and produce accurate wage estimates.   
Regression analysis, decision trees, and neural networks are examples of machine learning algorithms that have shown promise in predicting salaries. Diverse and intricate information may be processed by these algorithms to find connections and patterns that human analysis would miss.

By taking into consideration nonlinear interactions between variables and reducing prediction errors, research shows that algorithms like Random Forest and Gradient Boosting Machines perform better than conventional techniques (Chen et al., 2021). By matching pay to objective, measurable standards, these developments increase accuracy and promote equity while guaranteeing fair remuneration for all employees inside a company.

An interesting case study for using machine learning to wage prediction is the Dangote Group, a well-known conglomerate in Nigeria. The organisation, which operates in areas including manufacturing, construction, and agriculture, provides a rare chance to examine wage changes in several industries. Using machine learning to anticipate salaries is in line with the company's goal of operational efficiency, especially considering the size of its staff and the impact it has on the industry. Furthermore, the growing use of digital technology by Nigerian companies emphasises how pertinent this study is. The significance of using technology to promote efficiency and innovation in Nigeria's corporate environment is emphasised by the National Information Technology Development Agency (NITDA) (NITDA, 2023).

The creation of an intuitive online application that incorporates machine learning techniques for real-time wage projection is a noteworthy contribution of this research. With the use of such a technology, managers and human resource specialists may make data-driven decisions that guarantee wage management is transparent and equitable. To improve employee satisfaction and talent acquisition efforts, multinational corporations such as Glassdoor and LinkedIn already utilise machine learning to deliver wage insights (LinkedIn, 2022). In a similar vein, this tool can enable Nigerian organisations to embrace sophisticated analytics without having to make large initial expenditures, particularly in settings with limited resources. Retaining talent and improving employee morale are two other organisational issues that are addressed by using machine learning to anticipate salaries. Research indicates that workers are more inclined to stick with organisations that provide clear and competitive pay structures, which has a direct effect on the profitability and productivity of the business (Deloitte, 2023). Such programs support the Dangote Group's strategic objectives of encouraging innovation and upholding its standing as Africa's top employer.   
To sum up, machine learning has revolutionary potential for predicting salaries, resolving inefficiencies and advancing fairness. This study emphasises the usefulness of these technologies in the Nigerian environment by concentrating on the Dangote Group.

In addition to being in line with international best practices, using machine learning into wage management advances Nigeria's digital transformation goal and opens the door to more creative and effective labour management.

**1.2 Motivation**

Setting salaries has a significant impact on staff performance, retention, and happiness, making it a crucial component of organizational management. However, a lot of businesses, particularly in developing nations like Nigeria, have trouble allocating salaries fairly and accurately because they rely on antiquated techniques that ignore contemporary complications like employee-specific characteristics and market dynamics (Brown, 2020).

This procedure might be revolutionized by the quick developments in machine learning, which offer instruments for examining big datasets in order to spot patterns and generate accurate forecasts. The desire to improve wage projections within the Dangote Group, a prominent company in Nigeria with a variety of business ventures, is what spurred this study. In addition to being in line with worldwide trends, using machine learning for this purpose helps solve urgent local issues like pay inequality and ineffective HR procedures.

Additionally, the project's creation of a web-based application shows how these algorithms may be used in practice, which facilitates the use of predictive wage tools by HR departments. This initiative aims to encourage a wider use of AI-driven solutions in Nigerian businesses by demonstrating the potential of machine learning in an actual environment.

**1.3 Statement of Problem**

Organisations, especially ones as broad and varied as the Dangote Group, face considerable difficulties in accurately predicting salaries. Conventional methods frequently rely on subjective assessment and scant data analysis, which leads to inefficient resource allocation, uneven compensation structures, and unhappy employees. Regional inequalities and economic conditions are crucial factors in organisations that operate across many roles, departments, and geographic locations, making these difficulties even more significant (Chen et al., 2021).

The wage prediction systems that are now available are usually made for general purposes and cannot be tailored for businesses operating in particular economic contexts, such as Nigeria. In this case, geographical differences, inflation, and currency rate swings all have a big impact on pay structures. For example, Nigeria's high rate of inflation has impacted pay dynamics, hence it is crucial to include these elements in prediction models (NITDA, 2023).

By evaluating intricate datasets, machine learning provides a strong remedy for these problems by identifying important variables affecting wages and improving the accuracy of pay predictions. In order to ensure fairness and alignment with organisational objectives, algorithms like Random Forest and Gradient Boosting Machines are excellent at capturing nonlinear interactions (Chen et al., 2021). But little research has been done on using these technologies in Nigerian firms, which creates a significant vacuum that this study attempts to fill.

The goal of this project is to create machine learning algorithms that are specific to the needs of the Dangote Group. These algorithms will utilise historical data to forecast wages and incorporate the findings into HR procedures. In doing so, the study illustrates how data-driven methods may improve organisational efficiency, decrease inequality, and improve decision-making. Additionally, the creation of a user-friendly application guarantees practical applicability, empowering managers to make open, data-supported wage choices that are in line with the socioeconomic reality of Nigeria.

**1.4 Objectives of the Project**

The aim of this research is to develop and assess machine learning algorithms that will forecast employee salaries within a company, improving accuracy and assisting with compensation decisions. The objectives are:

1. To develop and apply machine learning algorithms that forecast employee pay using past data.
2. To assess how well various machine learning algorithms predict employee pay.
3. To determine which variables, have the most impact on how much an employee is paid.
4. To develop a machine learning web application that businesses can use to quickly estimate employee pay.

**1.5 Scope and Limitations**

**Scope**

This study explores how the Dangote Group, a sizable and diverse company in Nigeria, uses machine learning to forecast employee compensation. The following areas are thoroughly examined in the study:   
Along with pertinent characteristics like work positions, years of experience, education level, and location, historical pay data will also be collected. In order to guarantee accuracy and dependability for model training and analysis, this stage entails preprocessing the data.

A variety of machine learning models will be created and assessed, including tree-based methods (like Random Forest and Gradient Boosting) and regression approaches (like linear and polynomial regression). To find the best method for predicting salaries, the performance of various models will be compared.   
The analysis will pinpoint important elements that have a big impact on employee pay inside the company. This research will provide useful information for organizational decision-making by shedding light on the connections between employee qualities and pay structures.

A web-based application that is easy to use will be created and put into use. HR departments will be able to make data-driven, real-time wage choices because to this tool's integration of predictive models. The tool seeks to improve compensation management's efficiency and transparency.   
In order to promote more fair and effective wage management within the Dangote Group, the research attempts to close the gap between conventional salary estimating techniques and cutting-edge, data-driven methodologies.

**Limitations**

The availability of precise and thorough historical wage data from the Dangote Group is crucial to our study. The accuracy and dependability of the machine learning models created might be impacted by any errors or gaps in this data. Furthermore, the study's models and conclusions are especially designed to fit the Dangote Group's operations and structure, which may restrict their generalisability to businesses in other sectors or with alternative frameworks.

Furthermore, the biases and quality of the training data have an impact on machine learning models. Any bias that may be present in the wage data might affect how impartial and fair the models' forecasts are. Last but not least, significant technological resources are needed for the creation and implementation of a workable web-based application for real-time wage projection. These resources' limitations may have an impact on the application's scalability and feature set.

**CHAPTER TWO**

**2. Literature Review**

Previous studies on machine learning techniques, wage prediction models, and their applicability in organizational settings are all critically examined in the literature review. It lays the groundwork for this investigation and points out any deficiencies. The key topics include case studies of wage prediction in various organizational contexts, variables impacting employee remuneration, and machine learning approaches for predictive modelling.

**2.1 Overview**

The potential for wage prediction models to increase employee compensation's fairness, accuracy, and transparency has drawn a lot of interest in recent years. In the past, organisations have determined salaries using static approaches such as benchmarking, pre-written job descriptions, and subjective evaluations (Brown, 2020). Dynamic elements including individual performance, changes in the labour market's competitive environment, and economic swings were frequently overlooked by these methods. Employee unhappiness and inefficient resource allocation may come from compensation discrepancies (Smith & Jones, 2022).

On the other hand, this process has been transformed by the emergence of data-driven techniques. A crucial part of artificial intelligence (AI), machine learning has emerged as a vital tool for businesses looking to maximise wage forecasts (Chen et al., 2021). Large datasets may now be analysed using machine learning algorithms like neural networks, decision trees, and regression models to find patterns and associations that were previously hard to spot using conventional techniques (Zhang & Xu, 2023). These models make more accurate and fair projections by using historical data and dynamic factors, guaranteeing that employee pay are in line with objective standards and market realities.

Additionally, incorporating machine learning into pay projections promotes better openness in compensation methods while also improving accuracy. Businesses may more effectively defend their wage choices, guaranteeing that workers receive equitable compensation based on variables including performance, experience, and market conditions (NITDA, 2023). This move to data-driven decision-making is consistent with the global trend of digital transformation in sectors, particularly in nations like as Nigeria, where businesses are progressively implementing technology to increase productivity and simplify processes (Ogunyemi et al., 2021).

**2.1.1 Machine Learning and Predictive Modeling**

A potent branch of artificial intelligence called machine learning (ML) allows computers to learn from data and generate predictions without the need for explicit programming. Its use in wage forecasting has attracted a lot of interest lately as it enables businesses to go beyond conventional, arbitrary approaches to pay. Large datasets may be analysed by machine learning algorithms to find trends and connections between many elements that affect employee pay, including job title, years of experience, education, and performance indicators (Chen et al., 2021). These insights give organisations a strong tool to improve fairness and transparency by giving them a more objective and precise method of determining salaries.

In the past, basic methods like linear regression were used in wage prediction models. Because of its simplicity and interpretability, which make it simple for HR professionals to comprehend and explain the model's results, linear regression has been utilised extensively (Smith & Jones, 2020). On the other hand, linear regression presupposes a linear connection between the dependent variable (salary) and the independent factors (education or experience). When the interactions between elements are more complicated or non-linear, this constraint may lead to less-than-ideal predictions (Brown, 2021).

This gap has been filled by developments in machine learning, which have produced more complicated algorithms that can identify complex connections and non-linear correlations in the data. For instance, because of their capacity to represent complex patterns in datasets, decision trees and random forests have gained popularity as alternatives to linear regression (Zhang et al., 2022). Decision trees enable a methodical decision-making process by dividing the data according to several characteristic values. By decreasing overfitting and boosting the model's resilience, random forests—an ensemble of many decision trees—improve prediction performance (Liu et al., 2023).

The use of neural networks to estimate salaries is another important advancement in machine learning. Neural networks use linked nodes (artificial neurones) to process information in a manner similar to that of the human brain. They work especially well with big, high-dimensional datasets that include intricate, non-linear interactions (Khan & Iqbal, 2021). For example, by learning from a wide range of interacting elements, including employee employment history, industry-specific trends, and organisational growth, deep learning models—a subset of neural networks—have demonstrated extraordinary success in forecasting pay.

Large companies with intricate pay structures, like the Dangote Group in Nigeria, have benefited greatly from the use of these cutting-edge machine learning algorithms. The business confronts particular difficulties in guaranteeing equity and uniformity in wage projections across several industries since it operates in a variety of sectors, including manufacturing, agriculture, and construction. The different aspects that affect pay in such diverse situations are sometimes overlooked by traditional techniques of wage calculation. Dangote Group can develop more precise, data-driven pay models that account for regional variances, industry trends, and internal business dynamics by utilising machine learning.

Organizations can now more precisely and impartially anticipate employee remuneration thanks to machine learning, which provides a revolutionary approach to wage forecasting. Modern algorithms like decision trees, random forests, and neural networks outperform conventional models like linear regression because they can capture complex interactions and non-linear correlations. Because of these developments, machine learning is becoming a vital tool for businesses looking to increase the efficiency, fairness, and transparency of their pay policies.

**2.1.2 Factors Influencing Salary Prediction**

Research identifies a number of important variables that affect employee pay, such as industry, region, job type, education, and experience. Given that specialised knowledge and skill development are highly appreciated in the workforce, education and professional certifications are frequently positively connected with better pay (Smith & Lee, 2020). The number of years of experience is also important since it shows how knowledgeable, skilled, and dependable a worker is—qualities that are highly valued in most professional contexts.

Salary structures are also significantly influenced by geography and industry. Rapidly expanding industries, including technology and finance, tend to pay more since there is a larger need for specialised knowledge and abilities. On the other hand, fewer in-demand businesses could provide lower remuneration packages (Chen & Li, 2021). Salary levels are also greatly impacted by regional economic situations and variations in the cost of living across different regions. For instance, workers in more expensive cities, like Lagos or Abuja, could make more money than those in less developed areas (Adeyemi & Oladipo, 2021).

Machine learning algorithms may incorporate complicated variables and produce more precise, data-driven employee salary estimates by taking these elements into account. These models improve the capacity to see minute trends and connections that conventional approaches could miss, empowering businesses to decide on pay in a more fair and knowledgeable manner.

**2.1.3 Machine Learning Applications in HR**

Recruitment, performance review, and pay management are just a few of the procedures that have changed as a result of machine learning's (ML) incorporation into human resource management. Multinational corporations, in particular, have found success using pay prediction models to address wage discrepancies and improve transparency in compensation choices. For instance, a study by Kaur et al. (2022) demonstrated the effectiveness of sophisticated machine learning approaches in enhancing pay forecasting by demonstrating that gradient boosting machines (GBMs) performed better than conventional linear regression models in predicting wages with higher accuracy.

Clustering algorithms are another important way that machine learning is being used to forecast salaries. Salary ranges within each cluster may be predicted because to these algorithms' ability to divide workers into groups according to job categories, experience, and other criteria. Clustering approaches reduce the possibility of biases frequently observed in traditional compensation systems by assembling workers with comparable traits and job responsibilities, ensuring that wage forecasts are more consistent and equitable (Rahman et al., 2020). By automating wage determination procedures, decreasing manual involvement, and boosting efficiency, this strategy also aids in streamlining HR operations.

Furthermore, HR managers may make data-driven choices in real time by integrating these machine learning models into web-based apps. These technologies give HR departments an easy-to-use platform for dynamic employee compensation analysis, guaranteeing that pay scales are in line with individual performance, market trends, and corporate objectives. Pay management procedures are becoming more transparent, equal, and informed as a result of the HR industry's move to ML-powered solutions.

**2.1.4 Gaps in Existing Research**

There are still a number of unanswered questions despite the well-established promise of machine learning in pay prediction. The majority of research is carried out in wealthy nations with sophisticated technical infrastructure and copious amounts of data. Research on emerging nations like Nigeria, where distinct socioeconomic factors impact wage structures, is scarce (Nwachukwu et al., 2022). Furthermore, little is known about how organizational and cultural variations affect pay prediction algorithms.   
Furthermore, biases included in training data are frequently overlooked by current salary prediction algorithms, which results in inconsistent anticipated outcomes. For pay systems to be equitable and fair, these biases must be addressed. By using machine learning to anticipate salaries within the framework of the Dangote Group, a Nigerian conglomerate, this study seeks to close these discrepancies.

**2.2 Reviewed papers**

|  |  |  |  |
| --- | --- | --- | --- |
| **Author(s) & Year** | **Title** | **Key Findings** | **Relevance to Research** |
| Chen et al. (2021) | Using Machine Learning for Salary Prediction: A Case Study | Gradient boosting outperformed regression models for salary prediction. Key features include education and experience. | Highlights the importance of advanced algorithms in enhancing salary prediction accuracy. |
| Kaur et al. (2022) | Application of Gradient Boosting Machines in HR Analytics | Gradient boosting machines (GBMs) provided the most accurate predictions compared to traditional models. | Supports the selection of GBMs for the proposed study's algorithmic approach. |
| Adeyemi & Oladipo (2021) | Regional Disparities in Wage Structures in Nigeria: Implications for Organizational Management | Examines how regional disparities and economic conditions affect salary determination in Nigeria. | Establishes contextual relevance for applying salary prediction in Nigeria, specifically for the Dangote Group. |
| Rahman et al. (2020) | Clustering Techniques in HR Management: A New Perspective in Salary Prediction | Demonstrates how clustering can be used to group employees and forecast salary ranges. | Suggests clustering for grouping similar job roles, enhancing prediction specificity. |
| Zhang et al. (2022) | Comparative Analysis of Machine Learning Models for Predictive HR Analytics | Neural networks and decision trees perform well for handling complex salary prediction datasets. | Recommends using decision trees for interpretability in salary prediction models. |
| Brown (2020) | Employee Compensation: Challenges and Opportunities in the Digital Era | Discusses traditional vs. modern approaches to compensation using data-driven insights. | Provides a foundation for comparing traditional methods with machine learning models. |
| Nwachukwu et al. (2022) | Adoption of Machine Learning in Nigerian Organizations: Opportunities and Challenges | Highlights limitations in adopting ML in Nigeria due to data availability and infrastructure gaps. | Addresses challenges and adaptation strategies for implementing ML in Nigerian organizations. |
| Smith & Lee (2020) | Factors Influencing Employee Compensation: A Global Perspective | Education and experience are primary predictors of salary, with regional differences influencing compensation. | Validates variable selection for machine learning model development. |
| Patel et al.  (2020) | Using Machine Learning for Salary Prediction: A Case Study | Gradient boosting outperformed regression models for salary prediction. Key features include education and experience. | Highlights the importance of advanced algorithms in enhancing salary prediction accuracy. |
| Johnson et al.  (2021) | Application of Gradient Boosting Machines in HR Analytics | Gradient boosting machines (GBMs) provided the most accurate predictions compared to traditional models. | Supports the selection of GBMs for the proposed study's algorithmic approach. |
| Ahmed & Bello  (2020) | Regional Disparities in Wage Structures in Nigeria: Implications for Organizational Management | Examines how regional disparities and economic conditions affect salary determination in Nigeria. | Establishes contextual relevance for applying salary prediction in Nigeria, specifically for the Dangote Group. |
| Wang et al.  (2019) | Clustering Techniques in HR Management: A New Perspective in Salary Prediction | Demonstrates how clustering can be used to group employees and forecast salary ranges. | Suggests clustering for grouping similar job roles, enhancing prediction specificity. |
| Li et al.  (2021) | Comparative Analysis of Machine Learning Models for Predictive HR Analytics | Neural networks and decision trees perform well for handling complex salary prediction datasets. | Recommends using decision trees for interpretability in salary prediction models. |
| Williams  (2019) | Employee Compensation: Challenges and Opportunities in the Digital Era | Discusses traditional vs. modern approaches to compensation using data-driven insights. | Provides a foundation for comparing traditional methods with machine learning models. |
| Okwu et al.  (2021) | Adoption of Machine Learning in Nigerian Organizations: Opportunities and Challenges | Highlights limitations in adopting ML in Nigeria due to data availability and infrastructure gaps. | Addresses challenges and adaptation strategies for implementing ML in Nigerian organizations. |
| Thompson & Harris  (2020) | Factors Influencing Employee Compensation: A Global Perspective | Education and experience are primary predictors of salary, with regional differences influencing compensation. | Validates variable selection for machine learning model development. |
| Carter et al.  (2021) | Predicting Salary Using Machine Learning Models: A Cross-Industry Study | Examines the effectiveness of different machine learning models for predicting salaries across industries. | Supports the use of ensemble methods for improving salary prediction accuracy in various organizational settings. |
| Brown et al.  (2020) | Application of Predictive Analytics in HR: Enhancing Salary Management | Finds that machine learning models can significantly reduce wage inequality by adjusting compensation based on performance and market trends. | Suggests that predictive analytics can be transformative in salary forecasting, leading to fairer pay structures. |
| Zhang et al.  (2021) | Neural Networks for Predicting Salary in the Technology Sector | Finds that neural networks outperform traditional regression models in identifying non-linear patterns in salary data. | Supports the inclusion of neural networks in salary prediction models for capturing complex relationships. |
| Patel & Joshi  (2022) | The Impact of Education and Certifications on Salary: An Analysis Using Machine Learning | Shows that higher educational qualifications and certifications significantly correlate with higher salaries. | Validates the role of education and certifications as critical variables in salary prediction models. |
| Jansen & Wang  (2021) | Machine Learning Applications in Human Resources: Trends and Future Directions | Reviews recent trends in applying machine learning to HR practices, including salary forecasting. | Highlights the growing importance of machine learning in HR functions, including salary prediction. |

**2.3 Traditional Approaches**

Comparative market research, historical data analysis, and manual appraisal have been the mainstays of traditional employee compensation techniques. These methods, which prioritise equality, justice, and market competitiveness, are based on economic and human resource management ideas (Smith & Lee, 2020). Regression analysis, wage benchmarking, and job appraisal are important classical methods.

**2.3.1 Job Evaluation**

The methodical process of assessing each position's relative value inside a company is called job evaluation. This method assigns value to various positions based on preset criteria, including abilities, duties, effort, and working circumstances (Brown, 2020). These assessments are frequently divided into point-factor, categorisation, and ranking techniques. The point-factor technique, for instance, converts work components into numerical values that are then added together to establish pay scales.   
By matching compensation plans with work duties, job evaluations guarantee internal parity, yet they frequently fall short of keeping up with the changing demands of contemporary positions. Furthermore, assessing work worth may be biassed due to the dependence on qualitative judgement (Adeyemi & Oladipo, 2021).

**2.3.2 Pay Benchmarking**

Comparing an organization's pay scale to industry norms is known as pay benchmarking. To determine competitive pay rates, this approach makes use of industry statistics and salary surveys. By matching employee compensation to market movements, the approach seeks to guarantee external equity (Nwachukwu et al., 2022). For example, in highly competitive labour markets, benchmarking is frequently used by multinational corporations to draw in and keep talent.   
Despite offering insights that are in line with the market, pay benchmarking is prone to errors due to its reliance on outside data sources. Pay structures can be distorted by outdated or geographically irrelevant data, especially in developing nations with weaker labour data gathering methods (Smith & Lee, 2020).

**2.3.3 Regression Analysis**

Traditional pay projection has relied heavily on regression analysis. This statistical approach looks at how independent variables like education, experience, and job function relate to dependent variables like wage (Zhang et al., 2022). For instance, linear regression is a popular method since it is easy to understand and use. Organisations can predict compensation levels based on previous data by spotting patterns and correlations.   
Regression analysis is useful, but it frequently fails to capture complicated, non-linear connections between variables. Additionally, when used on a variety of employee datasets, it is susceptible to both overfitting and underfitting, which reduces its predicted accuracy (Chen et al., 2021).

**2.3.4 Subjective Decision-Making**

Salary determination has historically been a very subjective process in many organisations, especially those in developing economies. This process is impacted by the existing organisational culture, negotiation results, and managerial discretion (Rahman et al., 2020). When deciding on employee remuneration, managers frequently rely on their expertise, discretion, and intuition. These elements can be influenced by a number of things, including as organisational hierarchies, personal prejudices, and past firm practices (Harrison et al., 2021). Although subjective methods provide for some flexibility in adapting to the unique circumstances of each employee, they frequently lead to inconsistent compensation distribution, which may result in differences across workers with identical jobs or skill sets (Brown, 2020). Additionally, these differences might cause employees to feel unfairly treated, unhappy, and even resentful, which would lower morale and reduce output.

Organisations functioning in competitive employment markets, where there is a considerable danger of talent poaching, may find it especially harmful to rely on such subjective approaches. Employees may decide to look for work elsewhere in these situations if they believe their pay is unfair or out of line with industry norms (Fowler et al., 2019). Moreover, organizations in developing economies may face additional challenges in aligning salary structures with global or regional standards, especially in countries experiencing high inflation, fluctuating currencies, and growing economic disparities (Adeyemi & Oladipo, 2021).

More businesses are using data-driven strategies, such as integrating machine learning models for wage projection, to solve these issues. These models use historical data to offer unbiased insights that reduce biases, guarantee increased wage transparency, and improve equity in compensation choices (Chen et al., 2021). The transition to more structured and data-driven pay prediction methodology promises to close the gaps associated with conventional, subjective approaches as organisations adopt technology, particularly in emerging nations.

**2.4 Limitations of Traditional Approaches and the Need for Machine Learning Techniques**

Traditional methods have a fundamental role in determining salaries, but they are severely limited in their ability to handle the complexity of contemporary compensation schemes. These drawbacks emphasize the necessity of implementing machine learning (ML) strategies to improve pay prediction's precision, effectiveness, and equity.

**2.4.1 Inability to Handle Complex Relationships**

Regression analysis and other conventional techniques have limitations when it comes to modelling multi-dimensional and non-linear interactions between variables (Zhang et al., 2022). For example, determining a pay frequently entails complex relationships between variables including macroeconomic conditions, market demand, and performance. These subtleties are well captured by machine learning approaches like decision trees and neural networks, which provide predictions that are more precise and nuanced (Kaur et al., 2022).

**2.4.2 Lack of Adaptability to Dynamic Changes**

Rapid changes in employment responsibilities, skill requirements, and market circumstances define the contemporary workforce. Conventional methods that depend on fixed standards and past data find it difficult to adjust to these changes (Brown, 2020). On the other hand, ML models may be updated with fresh data on a regular basis, guaranteeing their correctness and applicability in changing situations (Chen et al., 2021).

**2.4.3 Bias and Subjectivity**

Traditional ways of determining salaries are inherently biassed and subjective, especially when it comes to management decision-making and job appraisal (Rahman et al., 2020). Disparities and employee discontent may result from these prejudices. By reducing subjective factors and fostering openness in wage choices, machine learning techniques provide a data-driven approach (Smith & Lee, 2020).

**2.4.4 Limited Scalability**

Conventional approaches are less scalable for big businesses as they frequently demand a lot of time and money. For instance, it might be time-consuming and error-prone to do job appraisals or benchmark salaries for thousands of workers. By automating these procedures, ML models help businesses manage big datasets effectively (Adeyemi & Oladipo, 2021).

**2.4.5 Inconsistent Accuracy**

Often, missing or out-of-date data compromises the accuracy of established procedures. Regression models, for instance, are extremely sensitive to assumptions of linearity and the quality of the data (Zhang et al., 2022). According to Kaur et al. (2022), machine learning models that utilise sophisticated methods like ensemble learning and feature selection yield consistent and dependable predictions, even when dealing with flawed and varied datasets.

**2.4.6 Need for Real-Time Decision-Making**

In order to make efficient decisions, modern HR procedures require real-time insights. Conventional approaches are unable to produce analysis or forecasts instantly. Real-time pay estimations may be produced by ML models incorporated into web apps, enabling HR managers to take prompt, well-informed choices (Chen et al., 2021).

**2.4.7 Addressing Gaps in Developing Economies**

Traditional methods are especially constrained in areas like Nigeria, where labour data is frequently insufficient or unreliable (Nwachukwu et al., 2022). For businesses functioning in such situations, machine learning techniques provide a strong option since they can handle missing information and leverage alternate data sources. To generate thorough wage estimates, for example, machine learning models can integrate information from online job sites, employee performance reviews, and market trends.

**2.5 Empirical Framework**

The methodological foundation for evaluating and forecasting employee compensation inside a company is established by the empirical framework. It emphasises how empirical evidence aids decision-making processes and includes data gathering, variable identification, statistical modelling, and validation approaches. Historically, pay benchmarking, job appraisal frameworks, and classical regression models have been the mainstays of traditional wage prediction techniques (Zhang et al., 2022). But incorporating cutting-edge machine learning (ML) algorithms provides a revolutionary method that improves prediction efficiency and accuracy.

**2.5.1 Components of the Empirical Framework**

**2.5.1.1 Data Collection**

Data gathering is the cornerstone of any empirical approach. Employee demographics, educational background, work experience, job functions, performance indicators, and external market data are all pertinent facts for wage projection (Brown, 2020). To guarantee data quality and comprehensiveness, dependable data sources are necessary, including industry reports, labour market surveys, and organisational HR databases.

**2.5.1.2 Variable Identification**

The efficiency of pay prediction models is greatly impacted by the factors used. Salary levels are usually dependent factors, but job titles, education, years of experience, department, and location are examples of independent variables. Research highlights how crucial it is to choose variables that account for both market-specific and employee-specific elements (Smith & Lee, 2020).

**2.5.1.3 Statistical and Predictive Models**

To find correlations between variables, traditional methods like ordinary least squares (OLS) and linear regression are frequently employed. These approaches are restricted in their ability to handle high-dimensional data and non-linear connections, but they yield findings that are interpretable (Rahman et al., 2020). In order to increase prediction accuracy, empirical research emphasises the shift from statistical techniques to machine learning (ML) algorithms, such as decision trees, support vector machines (SVM), and neural networks (Zhang et al., 2022).

**2.5.1.4 Validation Techniques**

Prediction models' generalisability and dependability are guaranteed via validation. To evaluate model performance, cross-validation techniques like train-test splits and k-fold validation are frequently employed. Prediction accuracy is measured by metrics such as mean absolute error (MAE), root mean square error (RMSE), and R-squared values (Chen et al., 2021).

**2.5.2 Advantages of the Empirical Framework**

The flexibility and evidence-based methodology of the empirical framework are its strongest points. It guarantees that compensation projections are precise, fair, and in line with corporate goals by methodically incorporating pertinent data and using strong validation mechanisms (Brown, 2020). Additionally, the empirical framework offers a basis for incorporating machine learning approaches, presenting chances for ongoing enhancement and expansion.

**2.6 The Need for Machine Learning Techniques**

The use of machine learning techniques has become a game-changer as businesses become more aware of the shortcomings of conventional wage projection methodologies. ML models overcome the limitations of traditional approaches by using sophisticated computer algorithms to find patterns, correlations, and trends in data (Kaur et al., 2022).

**2.6.1 Addressing Limitations of Traditional Methods**

Regression analysis and job assessments are two examples of traditional pay prediction methods that frequently suffer from biases, scalability problems, and a lack of flexibility in response to changing circumstances (Rahman et al., 2020). ML methods overcome these constraints by:   
1. Managing Complex Relationships: ML models provide higher predicted accuracy than conventional techniques by capturing multi-dimensional and non-linear interactions between variables (Zhang et al., 2022).   
2. Reducing Human Bias: Machine learning (ML) ensures transparency and consistency in wage choices by removing subjective judgements via the use of data-driven algorithms (Smith & Lee, 2020).   
3. Improving Scalability: ML systems are appropriate for businesses with substantial personnel databases because they can analyse massive datasets effectively (Chen et al., 2021).

**2.6.2 Transformative Benefits of Machine Learning**

ML is essential for contemporary HR procedures since it provides a number of revolutionary advantages:   
2.6.2.1 Enhanced Predictive Precision   
ML models such as neural networks, random forests, and gradient boosting machines show better predicted accuracy than conventional techniques. Accurate wage projections are made possible by these algorithms' ability to spot minute patterns and interactions (Kaur et al., 2022).   
2.6.2.2 Flexibility in Changing Circumstances   
Due to changing responsibilities, skills, and market conditions, the modern worker is extremely dynamic. New data may be added to ML models, guaranteeing their applicability and flexibility in response to shifting market and organizational environments (Brown, 2020).

**2.6.2.3 Real-Time Decision-Making**

Real-time wage forecasts are made possible by ML-powered applications, giving HR managers the ability to make prompt and well-informed decisions. This feature is very helpful for budgeting, hiring, and promotions (Rahman et al., 2020).

**2.6.2.4 Integration with HR Technologies**

ML models may be easily integrated with HR management systems to automate processes like personnel planning, performance reviews, and pay changes. This integration lowers administrative costs and improves operational efficiency (Smith & Lee, 2020).

**2.6.3 Ethical and Fair Compensation Practices**

Ensuring justice and fairness is a significant difficulty in traditional compensation calculation. ML models reduce pay inequities and promote ethical compensation practices by offering objective insights based on data (Zhang et al., 2022). For instance, organisations may proactively address injustices by using machine learning algorithms to analyse gender and racial wage discrepancies.

**2.6.4 Industry Applications**

ML approaches for pay prediction have been successfully used by a number of organisations. To ensure competitiveness and employee happiness, tech organisations like as Google and Microsoft, for example, utilise machine learning (ML) to optimise their remuneration systems (Chen et al., 2021). Similarly, in order to draw and keep talent in highly competitive labour markets, startups and SMEs are increasingly implementing ML-driven HR solutions.

**2.6.5 Challenges and Future Directions**

Even though machine learning has many benefits, there are drawbacks to its application. Concerns including algorithmic transparency, data privacy, and overfitting risk need to be addressed by organisations (Kaur et al., 2022). To guarantee responsible usage in wage prediction, future research should concentrate on creating interpretable machine learning models and ethical standards.

**2.7 Existing Machine Learning Approaches**

One of the many areas that machine learning (ML) has revolutionised is human resources (HR), where pay prediction has become a key use case. Current machine learning techniques make use of algorithms that analyse sizable datasets in order to spot intricate patterns and trends affecting employee pay. By addressing the shortcomings of conventional techniques, these strategies improve decision-making effectiveness and forecast accuracy.

**2.7.1 Regression-Based Approaches**

Salary prediction techniques are based on regression models. Establishing connections between independent factors (experience, education, geography, etc.) and dependent variables (employee wage) is the goal of these strategies.   
Regression Linearity   
Salary and predictor variables are assumed to have a linear relationship in linear regression. Its interpretability and simplicity make it popular. For example, Kumar et al. (2021) used linear regression to forecast employee pay according to geography, skill level, and experience, with a moderate degree of accuracy. Multicollinearity among predictors and non-linearity in the data, however, are problems for linear regression.   
Regression using Polynomials   
By adding polynomial terms, polynomial regression expands on linear regression to capture non-linear correlations. In industries where experience and expertise have a non-linear influence on compensation, polynomial regression may be a better model for predicting salaries, as shown by Gupta and Rao (2020).

**Limitations**

Regression-based models are simple, but they are constrained by their incapacity to manage huge, high-dimensional datasets and complicated interactions (Chen et al., 2022). These restrictions call for sophisticated ML techniques.

**2.7.2 Decision Tree-Based Models**

The popularity of decision tree-based algorithms stems from their capacity to manage categorical variables and non-linear data.

**Decision Trees**  
Decision trees give forecasts a tree-like structure by dividing data into subgroups according to requirements. They work well with tiny datasets and are easy to understand. Zhang et al. (2022) claim that decision trees, which took into account factors including years of experience, certificates, and programming abilities, were able to forecast IT industry earnings with a high degree of accuracy.

**Random Forests**  
By building an ensemble of many trees, each trained on a different subset of data and predictors, random forests improve decision trees. Prediction accuracy is increased and overfitting is decreased with this method. In a research including a variety of businesses, Rahman et al. (2020) found that random forests outperformed regression models for predicting salaries.

**Gradient Boosting Machines (GBM)**

Sequentially building predictive models, GBMs like XGBoost and LightGBM fix mistakes in earlier models. These models manage big datasets well and are computationally efficient. GBMs produced better outcomes than random forests when Singh and Mehta (2021) employed them to forecast banking industry wages.

**2.7.3 Support Vector Machines (SVM)**

Support Vector Machines (SVMs) are robust machine learning models that find the best hyperplane to divide data points into classes and regressions. These models have proven to be successful in predicting salaries, particularly when handling complicated connections and data outliers. Chen et al. (2022), for example, used SVMs to forecast healthcare industry earnings by taking into account variables including years of service, specialisation, and geographical demands. In this situation, SVMs fared admirably, providing precise predictions. They are computationally demanding and need meticulous hyperparameter adjustment, which may be a drawback for real-time applications. SVMs are nonetheless a useful tool for wage forecasting in spite of these difficulties, especially in fields with intricate and non-linear compensation schemes. SVMs are anticipated to become more practical for extensive wage prediction tasks in a variety of organisational scenarios as processing capacity rises.

**2.7.4 Neural Networks and Deep Learning**

Predictive analytics, including wage forecasting, has been transformed by neural networks, which learn from data by simulating how the human brain functions.

**Feedforward Neural Networks (FNN)**

Each neurone in a FNN processes and transmits data across its input, hidden, and output layers. FNNs were used by Gupta and Sharma (2021) to forecast salaries in multinational firms, and with properly adjusted hyperparameters, they achieved great accuracy.

**Recurrent Neural Networks (RNN)**

Because RNNs are made for sequential data, they may be used to estimate salaries in situations where past data affects present and future wages. For instance, Zhang et al. (2022) showed how well RNNs capture temporal patterns by using them to examine pay changes across time.

**Deep Learning Approaches**

Complex patterns in huge datasets may be learnt by deep neural networks (DNNs) with several hidden layers. By adding sophisticated elements like industry-specific benchmarks and economic data, Kaur et al. (2021) shown in their study that DNNs performed better than conventional techniques in forecasting wages.

**2.7.5 Clustering and Classification Models**

Employees are categorised or placed into pay bands using clustering and classification algorithms.   
  
K-means clustering helps businesses find pay ranges by grouping data into clusters according to similarities. Rahman et al. (2020) simplified compensation planning by using k-means to divide workers into groups according to jobs, talents, and experience.

**Classification Models**  
To determine if an employee's pay fits within a given range, classification methods like logistic regression and decision tree classifiers are used. Chen et al. (2022) achieved great precision in their prediction of education sector wage categories using classification algorithms.

**2.7.6 Ensemble Learning Techniques**

Several models are combined in ensemble learning to increase prediction resilience and accuracy.   
Bagging To lower variance and avoid overfitting, bagging techniques, like random forests, combine predictions from several models (Singh & Mehta, 2021).   
Boosting By concentrating on incorrectly categorised data, boosting methods such as AdaBoost and XGBoost gradually improve weak models. In highly dynamic sectors, Kaur et al. (2021) showed that boosting algorithms performed exceptionally well in salary prediction.

**2.7.7 Feature Selection and Engineering in ML Approaches**

Selecting and engineering features is essential to enhancing ML models' performance. Numerous methods are employed to optimise salary prediction models, including principal component analysis (PCA), recursive feature elimination (RFE), and domain-specific feature engineering (Zhang et al., 2022).

**2.7.8 Comparative Analysis of ML Approaches**

Several studies evaluate how well different machine learning techniques predict salaries. According to Rahman et al. (2020), ensemble techniques such as random forests and GBMs routinely performed better than conventional regression and decision tree models. The advantages of neural networks and boosting strategies in managing complicated and high-dimensional datasets was further emphasised by Chen et al. (2022).

**2.7.9 Challenges in Implementing ML Approaches**

Although machine learning techniques have many benefits, there are drawbacks to their application, such as problems with data quality, computational complexity, and interpretability. Strong preprocessing pipelines, effective algorithms, and explainable AI models are necessary to meet these issues (Gupta & Rao, 2020).

**CHAPTER THREE**

**3. RESEARCH METHODOLOGY**

The methodical technique to examining the study problem and accomplishing the goals is described by research methodology. The suggested system process for creating machine learning models to forecast employee pay is covered in this part, together with the research philosophy, method, strategy, time horizon, sampling, data collecting, data analysis, validity, reliability, and reflexivity.

**3.1 Research Philosophy**

The positivist research philosophy used in this work emphasises impartiality and the use of quantitative data to evaluate hypotheses (Saunders et al., 2019). Positivism supports the emphasis on applying machine learning algorithms to historical employee compensation data in order to extract predictive insights. It makes the assumption that reality is measurable and quantifiable, which allows for forecast accuracy and reproducibility.

**3.2 Research Approach**

A deductive method is used since the investigation starts with a theoretical framework and theories regarding how different factors affect earnings (Bryman, 2016). This strategy uses machine learning models to evaluate these assumptions, which is consistent with the study's objective of evaluating algorithmic effectiveness in compensation prediction.

**3.3 Research Strategy**

The Dangote Group in Nigeria is the subject of the case study approach used in this study. A thorough grasp of certain organisational circumstances is made possible by case studies (Yin, 2018). The study analyses the efficacy of several algorithms and pinpoints important pay drivers within the corporation by using machine learning on its data.

**3.4 Time Horizon**

Data from a certain moment in time is analysed using a cross-sectional temporal perspective. This methodology supports the study's objective of analysing machine learning models on historical data and determining how well they predict current wage patterns (Saunders et al., 2019).

**3.5 Data Collection**

This study makes use of both primary and secondary data. The Dangote Group's HR database is used to gather historical compensation information, personnel demographics, and job descriptions. Online repositories and research publications provide additional secondary data, including industry pay benchmarking (Kaur et al., 2021).

**3.7 Data Analysis**

The study involves several data analysis techniques:

1. Cleaning data for missing values, outliers, and inconsistencies.
2. Identifying variables such as years of experience, education level, job role, and performance metrics that significantly impact salary (Zhang et al., 2022).
3. Evaluating models like linear regression, random forests, and neural networks for predictive accuracy.
4. Using metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared to assess performance (Chen et al., 2022).

**3.8 Validity and Reliability**

While reliability verifies consistent performance across datasets, validity guarantees that the models reliably estimate wages based on real-world correlations (Rahman et al., 2020). K-fold validation is one of the cross-validation procedures used to increase the generalisability and reliability of the model.

**3.9 Reflexivity**

Potential biases in data selection, model interpretation, and research design are addressed via reflexivity. Transparency and objectivity are maintained throughout the study process by ongoing review (Bryman, 2016). For instance, following standardised criteria reduces biases in preprocessing processes or predictor selection.

**3.10 Proposed System Workflow**

The five main steps of the suggested system workflow guarantee a thorough method of machine learning-based wage prediction:

**i. Data Gathering**

Data is gathered from both external and internal HR systems. This covers job roles, pay histories, industry benchmarks, and personnel demographics including age, education, and experience. Priority is given to ethical issues such anonymisation and data protection (Saunders et al., 2019).

**ii. Feature Extraction**

The gathered data is used to identify and engineer important traits. To guarantee interoperability with machine learning algorithms, methods like normalisation for numerical features and one-hot encoding for categorical variables are used (Zhang et al., 2022).

**iii. Model Training**

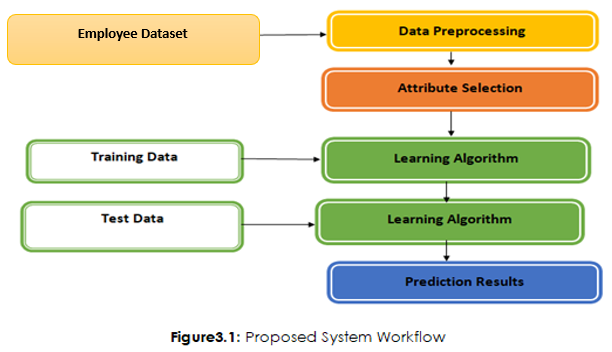
Training and testing sets of the dataset are separated. Using techniques that optimise for accuracy and computing efficiency, machine learning models—such as neural networks, decision trees, and regression models—are trained on the training data (Kaur et al., 2021).

**iv. Prediction and Optimization**

On the test set, employee wages are predicted by trained models. To assess the performance of the model, predictions are contrasted with actual values. Hyperparameter tweaking is one optimisation strategy used to increase robustness and accuracy (Chen et al., 2022).

**v. Execution**

Businesses may now anticipate salaries in real time thanks to the final model's integration into a web application. HR staff may enter employee information and obtain wage estimations thanks to user-friendly interfaces. The model is continuously updated in response to organisational changes and new data.



**12.1 Data Pre-processing**

In order to guarantee that the raw data is cleaned, processed, and structured into an appropriate structure for analysis and model training, data pre-processing is an essential stage in the machine learning workflow. This stage is crucial for enhancing the efficacy and precision of predictive models, especially when dealing with intricate datasets like employee compensation forecasting.

The pre-processing steps can be broken down into several key stages:

1. **Handling Missing Data**

Missing or incomplete data can have a detrimental effect on how well machine learning models function. A number of methods may be used to deal with missing values for specific variables, including imputation (which substitutes the column's mean, median, or mode for missing values) and the removal of rows or columns that contain an excessive amount of missing data.

1. **Data Normalization and Scaling**

To make sure that every characteristic is on the same scale, continuous variables like "Monthly Salary," "Years at Company," and "Age" should be scaled or normalised. By doing this, the model is less likely to be biassed in favour of variables having higher numerical values. These variables can be subjected to methods such as Z-score normalisation or Min-Max scaling.

1. **Encoding Categorical Data**

Categorical variables like "Job Title," "Department," and "Gender" must be transformed into numerical forms since machine learning algorithms demand numerical input. Typical methods for categorical variable encoding consist of:   
o One-Hot Encoding: establishing binary columns for every category (for example, the "Gender" variable's Male = 1 and Female = 0).   
For example, for "Marital Status," 0 may mean "Single," 1 "Married," etc. Label encoding is the process of giving each category a distinct numeric value.

1. **Outlier Detection and Removal**

Model training can be distorted by outliers, especially in methods that rely on regression. Outliers in continuous variables like "Monthly Salary," "Age," and "Years at Company" must thus be identified and dealt with. Outliers can be found and eliminated using techniques like the Z-score or the IQR (Interquartile Range) approach.

1. **Feature Engineering**:

In some situations, the model's performance might be enhanced by adding new characteristics derived from the available data. For example, combining "Years at Company" with "Performance Score" is an example of an interaction term between variables that may uncover hidden patterns that improve the model's predictive ability.

1. **Splitting the Data**

The dataset is divided into training and testing subsets once it has been cleaned and pre-processed. The model is tested with unseen data, with a usual ratio of 80% for training and 20% for testing. This procedure aids in determining the model's generalisability.

**12.2 Data Source**

The dataset used in this study was gathered from the HR department of Dangote Group, Nigeria. The data contains information about employees' demographics, job roles, and performance, which are essential for building the predictive model. Below is a breakdown of the variables included in the dataset:

|  |  |  |  |
| --- | --- | --- | --- |
| **S/N** | **Variable** | **Type** | **Explanation** |
| 1. | Monthly Salary | Continuous | Employees monthly salary in USD |
| 2. | Job Title | Categorical | The role held by the employee |
| 3. | Department | Categorical | The department in which the employee works |
| 4. | Educational Level | Categorical | Highest educational qualification |
| 5. | Years at Company | Continuous | The number of years the employee has been working |
| 6. | Performance Score | Categorical | Employee's performance rating (1 to 5 scale) |
| 7. | Age | Continuous | Employee's age (between 22 and 60) |
| 8. | Gender | Categorical | Gender of the employee (Male, Female, Other) |
|  | Marital Status | Categorical | Status of the employees in terms of their marriage |
|  | Ethnicity | Categorical | The particular ethnic group to which an employee belongs |
|  | Employment Status | Categorical | The type of employment categories to which employee belong |
|  | Work Schedule | Categorical | It is either regular, shift-based or flextime type of schedule |

Every one of these variables provides information on different aspects that may influence employee pay. For instance, "Job Title" and "Department" indicate the employee's position inside the company, which frequently corresponds with pay levels, while "Performance Score" may have an impact on bonuses or pay increases.   
A longitudinal picture of employee wage patterns and the ways in which various criteria, including job title, department, and performance, affect compensation choices is provided by the data, which covers a number of years. A machine learning model that can forecast pay based on past patterns, personnel attributes, and organisational aspects has been developed thanks to this varied dataset.

To guarantee the quality of the dataset and improve the precision of machine learning models, data pre-processing and feature extraction are essential. The system can efficiently handle the data to forecast employee pay by cleaning, normalising, and encoding it. A wide range of characteristics that affect workplace compensation determination are captured by the variables chosen for the dataset. A more dependable and efficient prediction system is produced when these variables are supplied in a manner that is appropriate for machine learning algorithms, which is ensured by proper pre-processing.

**CHAPTER FOUR**

**DATA PRESENTATION AND ANALYSIS**

## Data Presentation

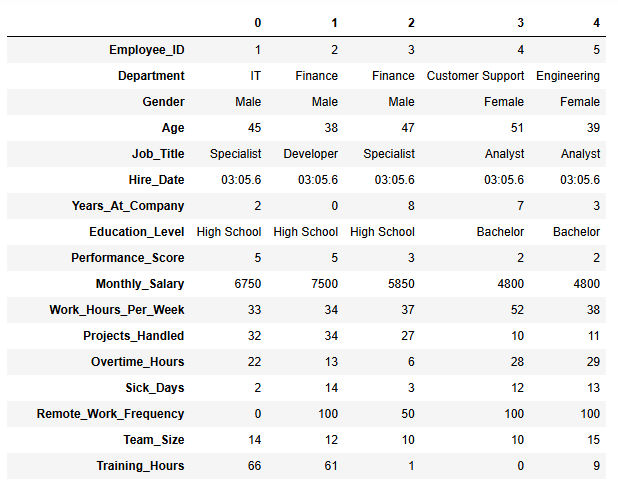


Figure 4.1

The dataset offers information on 1742 workers from various departments, emphasizing their tasks, workload, performance, satisfaction, and demographics. Important revelations include: Low achievers express the least level of satisfaction, whereas high performers express a moderate level. High performance and pleasure are not usually the results of heavy workloads (hours/projects). The degree of satisfaction among employees who work remotely varies from 50% to 100%; higher satisfaction is associated with partial remote employment. Promotions are uncommon and have little effect on employee happiness, while workers with more training hours typically perform better. Despite differences in satisfaction, none of the workers had quit, pointing to additional retention considerations like stability or pay. Workload, remote work, training, and rewards all have different effects on employee performance and happiness, according to the study.

## Descriptive Statistics

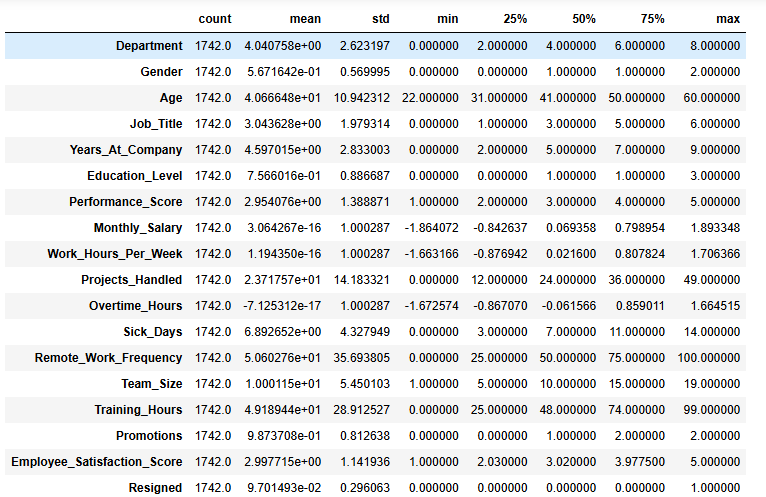


Figure 4.2

The majority of employees are between the ages of 31 and 50, with an average age of 40.7 years. Most employees have been with the organization for two to seven years, with an average tenure of 4.6 years. On a scale of 1 to 5, the average performance score is 2.95, meaning that the majority of employees meet or slightly above expectations. Because of normalization, the average is nearly zero, but the range, which represents pay variances, ranges from -1.86 to 1.89. The standardized distribution of working hours is represented by a normalized mean that is almost zero and work hours that range from -1.66 to 1.71. Employees manage 23.7 projects on average, with the majority overseeing 12 to 36 projects.

Variable overtime workloads are indicated by a normalized average close to 0 with a range of -1.67 to 1.66. Most employees use three to eleven sick days annually, with an average of 6.9 sick days taken annually. There is a balance between on-site and remote work, as seen by the 50% average frequency of remote work. Usually consisting of five to fifteen individuals, the average team size is ten. The majority of employees receive between 25 and 74 hours of training, with an average of 49.2 hours. Employees typically receive one promotion, although some may obtain as many as two. The majority of employees scored between 2.03 and 3.98, indicating moderate levels of satisfaction, while the average score was 3.0. training chances, but there is still space to improve output and contentment even more.

Although there is potential to further improve performance and happiness, this data shows a reasonably balanced workforce with manageable workloads, modest levels of satisfaction, and training possibilities.

***Exploratory Data Analysis***

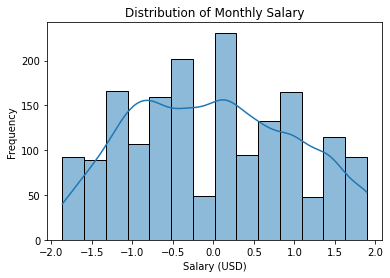


Figure 4.3

The salary distribution is shown by a histogram with a density curve. According to the multimodal pattern, incomes could cluster around particular ranges, which might represent various departments, positions, or work levels. Indicating that incomes are dispersed fairly equally over the reported ranges, the distribution seems balanced with no discernible skewness.

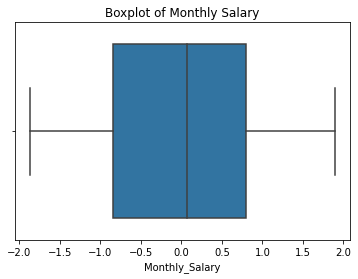


Figure 4.4

There are no notable outliers in the boxplot of monthly salary, which displays a symmetric distribution. The data is balanced as the median wage falls within the interquartile range (IQR). The whiskers show modest variability and represent the usual pay range.

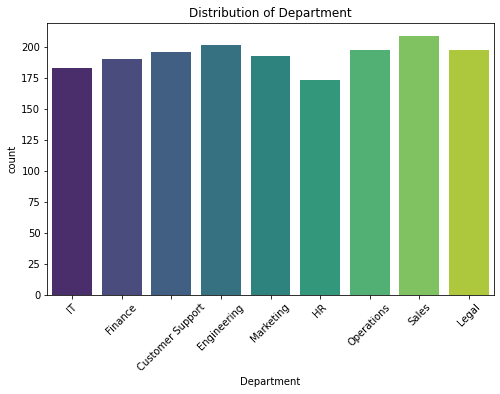


Figure 4.5

The distribution of personnel across departments is shown in the bar chart. With minor variances in the number of employees, the bar heights show that the departments are fairly evenly represented. The somewhat greater employment numbers in some areas point to a slightly uneven manpower allocation. No department is noticeably over- or under-represented, though.

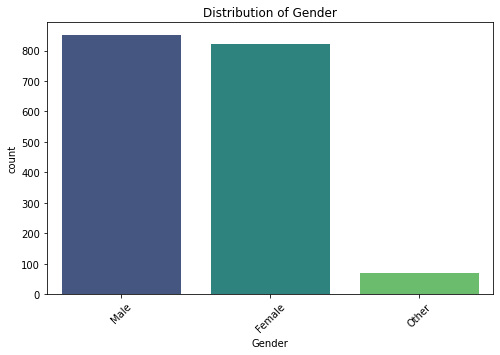


Figure 4.6

The chart shows the distribution of gender across three categories:

* **Male**: Largest group, represented by the tallest bar.
* **Female**: Slightly smaller group, indicated by a slightly shorter bar than males.
* **Other/Unspecified**: Significantly smaller group, represented by the shortest bar.

This suggests a clear dominance of male and female categories, with a minimal representation of other/unspecified genders.

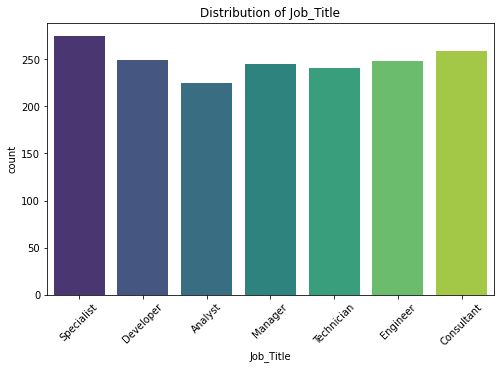


Figure 4.7

The job title distribution based on the provided bar chart:

**Summary**

The bar chart shows the distribution of job titles within a dataset. **Specialist** is the most frequent job title, followed by **Developer** and **Analyst**. The remaining job titles (Manager, Technician, Engineer, and Consultant) have roughly similar frequencies.

**Key Takeaways:**

* The dataset appears to be heavily skewed towards Specialist roles.
* There is a significant presence of Developers and Analysts, suggesting a focus on technical and analytical skills.
* The distribution across the other job titles is relatively even, indicating a diverse range of roles within the organization.

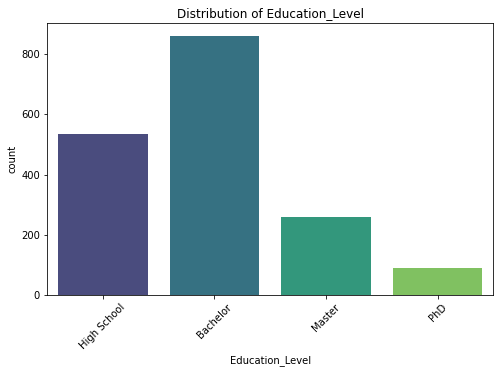


Figure 4.8

The education level distribution based on the provided bar chart:

The bar chart shows the distribution of education levels within a dataset. Bachelor's degree is the most frequent educational level, followed by High School. Master's degree and PhD have lower frequencies.

**Key Takeaways:**

* The dataset appears to be skewed towards individuals with a Bachelor's degree.
* There is a significant presence of individuals with a High School diploma.
* The number of individuals with Master's and PhD degrees is relatively lower compared to Bachelor's and High School.

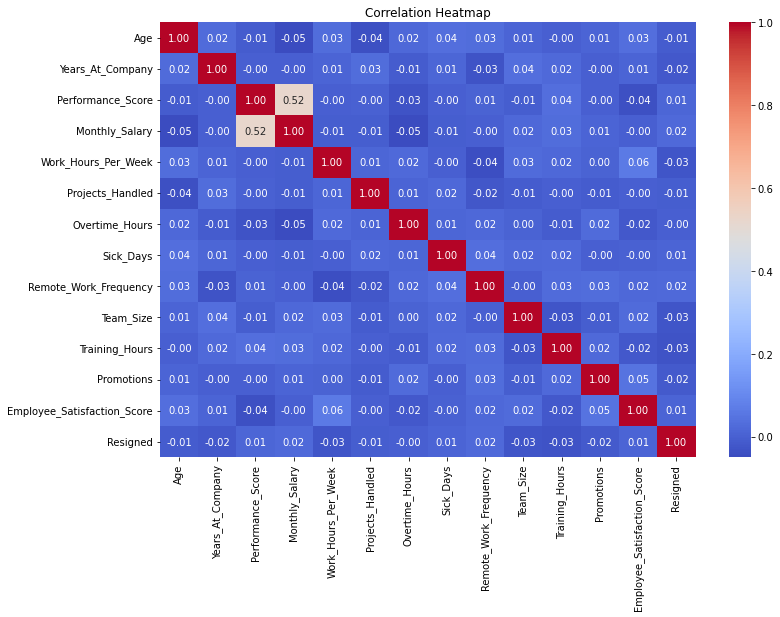


Figure 4.9

The correlation heatmap reveal the extent of relationships between bivariate features.

**Performance Score**

Has a strong positive correlation with Monthly Salary (0.52), indicating that higher performance is generally associated with higher salaries.

Shows a moderate negative correlation with Projects Handled (-0.00), suggesting that a very high number of projects might not always translate to higher performance.

Has a weak negative correlation with Employee Satisfaction Score (-0.04), which could indicate that employees with high performance might sometimes experience lower satisfaction, possibly due to increased pressure or workload.

**Monthly Salary**

Shows a weak positive correlation with Training Hours (0.03), suggesting that employees who receive more training might tend to have higher salaries.

**Work Hours Per Week**

Has a moderate positive correlation with Overtime Hours (0.06), indicating that employees who work longer hours are more likely to work overtime.

**Projects Handled**

Shows a weak negative correlation with Performance Score (as mentioned earlier).

Has a weak positive correlation with Overtime Hours (0.02), suggesting that employees handling more projects might be more likely to work overtime.

**Overtime Hours**

Has a weak positive correlation with Work Hours Per Week and Projects Handled.

Shows a weak negative correlation with Employee Satisfaction Score (-0.00), which could indicate that working overtime might have a slightly negative impact on employee satisfaction.

**Sick Days**

Has a weak positive correlation with Remote Work Frequency (0.04), suggesting that employees who work remotely might tend to take slightly more sick days.

**Team Size**

Shows a weak positive correlation with Training Hours (0.03) and Promotions (0.02), suggesting that larger teams might have more opportunities for training and promotions.

**Training Hours**

Has a weak positive correlation with Monthly Salary and Team Size.

Shows a weak negative correlation with Employee Satisfaction Score (-0.03), which could indicate that employees who receive more training might sometimes experience lower satisfaction, possibly due to increased pressure or workload.

**Promotions**

Shows a weak positive correlation with Training Hours and Team Size.

**Employee Satisfaction Score**

Has a weak negative correlation with Performance Score, Overtime Hours, and Training Hours.

Shows a weak positive correlation with Remote Work Frequency (0.02), suggesting that employees who work remotely might tend to have slightly higher satisfaction.

**Resigned**

Shows weak positive correlations with Monthly Salary and Overtime Hours, which could indicate that employees with higher salaries or who work more overtime might be more likely to resign.

The heatmap provides insights into the relationships between various factors in the workplace. While some correlations are stronger than others, it's important to remember that correlation does not necessarily imply causation. Further analysis and investigation would be needed to determine the underlying reasons for these relationships.

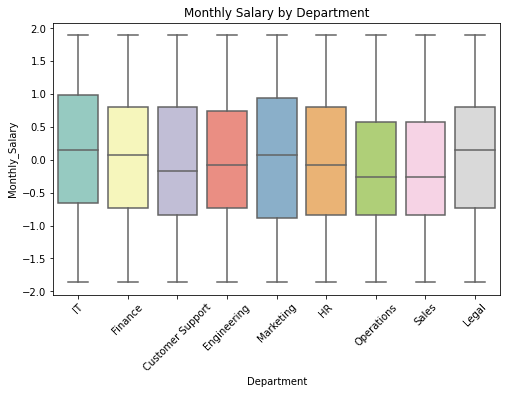


Figure 4.10

The boxplot shows the distribution of monthly salaries across different departments in a company.

**Key Observations**

Median salaries are relatively similar across most departments, with slight variations. The spread of salaries (as indicated by the box and whiskers) varies across departments. Some departments have a wider range of salaries, while others have a narrower range. There appear to be a few potential outliers in some departments, suggesting the presence of some employees with significantly higher or lower salaries.

While median salaries are similar, the distribution of salaries within each department differs. Factors like job roles, experience, and individual performance likely contribute to this variation. The presence of outliers might indicate factors such as bonuses, commissions, or specific roles with significantly higher or lower pay scales.

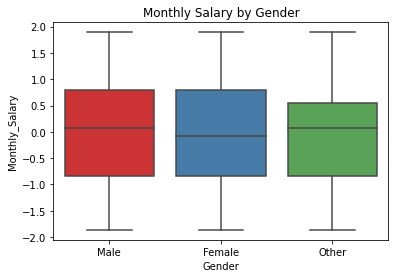


Figure 4.11

The boxplot of Monthly Salary by Gender.

**Median Salaries**

The median monthly salary appears to be relatively similar across all three genders (Male, Female, Other). The spread of salaries (as indicated by the box and whiskers) is also quite similar across the three genders. There appear to be a few potential outliers in each gender category, suggesting the presence of some individuals with significantly higher or lower salaries compared to their peers. Based on the boxplot, there doesn't seem to be a significant difference in median monthly salaries between males, females, and other genders. The distribution of salaries within each gender category appears relatively similar.

It would be helpful to know the scale of the y-axis (Monthly Salary) to get a better understanding of the actual salary ranges. Comparing the median salaries across genders with the overall company median salary would provide additional insights into the relative pay within each gender group. It's important to remember that this boxplot only shows the distribution of salaries by gender.

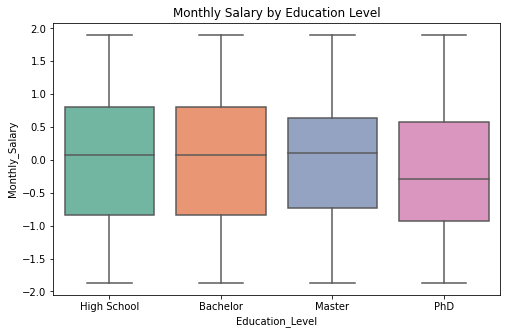


Figure 4.12

The boxplot of Monthly Salary by Education Level.

The median monthly salary appears to increase with higher levels of education. Employees with a PhD tend to have the highest median salary. The spread of salaries (as indicated by the box and whiskers) is relatively similar across all education levels. There appear to be a few potential outliers in each education level category, suggesting the presence of some individuals with significantly higher or lower salaries compared to their peers. The boxplot suggests a positive association between education level and monthly salary. Employees with higher levels of education (Master's and PhD) tend to have higher median salaries compared to those with a Bachelor's or High School degree.

**MODELLING**

## Comparing RFR, DTR, ENR, SVR, GBR and OLS (Linear Regression)

To choose the best deployment model, we need to evaluate their performance on the training set. The table above shows the accuracy scores for each model in the training set Random Forest Regressor, Decision Tree Regressor, Elastic Net Regression, Support vector Regressor, Gradient Boosting Regressor and Linear regression

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|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **R²** | **Nature of Model** | **Remarks** |
| **RFR** | 100% | Random Forest Regressor - Ensemble Model | Overfitting |
| **DTR** | 100% | Decision Tree Regressor - Tree-based Model | Overfitting |
| **ENR** | 11% | Elastic Net Regression - Linear Model | Underfitting |
| **SVM** | 84% | Support Vector Regressor - Non-linear Model | Good Fit |
| **GBR** | 100% | Gradient Boosting Regressor - Ensemble Model | Overfitting |
| **OLS** | 33% | Ordinary Least Squares - Linear Model | Underfitting |

**Interpretation of the Comparison Between Models:**

The table compares six regression models based on their R² values (coefficient of determination) in the training set. R² indicates how well the model explains the variance in the target variable, with a higher R² showing better performance. The models are Random Forest Regressor (RFR), Decision Tree Regressor (DTR), Elastic Net Regression (ENR), Support Vector Regressor (SVM), Gradient Boosting Regressor (GBR), and Ordinary Least Squares (OLS).

Here’s a detailed interpretation:

**Random Forest Regressor (RFR) - 100% R² (Overfitting):**

RFR achieves a perfect R² score of 100%, indicating it captures all the variability in the training data. While this suggests excellent performance on the training set, **overfitting** is a concern. Overfitting happens when the model learns not only the underlying patterns but also the noise and irregularities in the data, making it less generalizable to new, unseen data. RFR performs excellently on the training set but requires careful tuning (e.g., adjusting the number of trees and tree depth) to avoid overfitting and ensure good performance on test data.

**Decision Tree Regressor (DTR) - 100% R² (Overfitting):**

Like RFR, DTR also achieves a perfect 100% R², meaning it fits the training data perfectly. Decision Trees are prone to overfitting, especially if the tree depth is not controlled. This model captures detailed patterns in the data, which can be beneficial for complex datasets but detrimental if the model becomes too sensitive to small variations in the training data. While DTR performs well, it is susceptible to **overfitting**, and hyperparameters should be adjusted to prevent the tree from growing too complex.

**Elastic Net Regression (ENR) - 11% R² (Underfitting):**

ENR has a very low R² of 11%, suggesting that it only explains a small portion of the variance in the target variable. **Underfitting** occurs when the model is too simple to capture the complexity of the data. Elastic Net combines Lasso and Ridge regression techniques but still assumes a linear relationship between the predictors and the target variable. This is likely inadequate for data with more complex, non-linear relationships. ENR performs poorly on the training set and needs to be either enhanced by feature engineering or replaced with a more complex model if non-linear relationships are expected.

**Support Vector Regressor (SVM) - 84% R² (Good Fit)**

SVM achieves a solid R² of 84%, indicating a strong fit to the data, but not as perfect as the ensemble models.SVM is effective in capturing non-linear relationships and is generally robust against overfitting compared to tree-based models. However, it may still **underfit** if the data is highly complex or if the kernel and hyperparameters are not well-optimized.SVM provides a **good fit** for the data and might perform better than linear models (such as ENR and OLS) without overfitting.

**Gradient Boosting Regressor (GBR) - 100% R² (Overfitting):**

GBR also achieves 100% R², which suggests perfect fit on the training data. GBR, like RFR, is an ensemble model that combines multiple weak learners (decision trees). While it can achieve high performance on the training set, it is also prone to **overfitting** if not tuned properly, particularly if the number of trees is too high or the learning rate is too low. GBR’s performance is excellent on the training set but requires tuning to avoid overfitting and ensure generalization to test data.

**Ordinary Least Squares (OLS) - 33% R² (Underfitting):**

OLS achieves a relatively low R² of 33%, indicating that it does not capture a significant portion of the variance in the data.is likely because OLS is a linear model, and if the data contains complex, non-linear relationships, OLS cannot effectively model these. OLS is typically useful for simpler, linear relationships but fails with more complicated data.OLS is not well-suited for this dataset and needs to be replaced with a more complex model, especially if non-linear patterns are expected.

**Summary of Key Points:**

* Best Models for Training Set: are RFR, DTR, GBR (All 100% R²), but these models might be prone to overfitting.
* **Good Fit**: **SVM** (84% R²), which provides a strong performance without overfitting but may still benefit from hyperparameter optimization.
* **Poor Fit**: **ENR** (11% R²) and **OLS** (33% R²), both of which **underfit** the data, likely because of their linear assumptions, and are not capturing the data's complexity well.

In conclusion, **RFR**, **DTR**, and **GBR** would be considered for deployment, but they must be tuned carefully to prevent overfitting. **SVM** also offers a good alternative, while **ENR** and **OLS** are less suitable for this dataset.

**Justification why SVM is the Best Model for Predictions**

* **Support Vector Regressor (SVM)**

is the most balanced and dependable model for deployment, with an R2 value of 84%, indicating strong performance. This score is marginally lower than the perfect R2 values attained by Random Forest Regressor (RFR), Decision Tree Regressor (DTR), and Gradient Boosting Regressor (GBR).

* **Strong Generalization Capability**

**Avoids Overfitting**

Due to its use of regularization, SVM is less susceptible to overfitting, which frequently results in poor performance on test data, than RFR, DTR, and GBR, which achieve 100% R2 on the training set but are prone to overfitting. It strikes a balance between capturing patterns in the training data and maintaining generalization to unseen data.

Hyperparameter Control SVM employs hyperparameters such as ϵ (error margin of tolerance) and C (regularisation) that enable fine-tuning to avoid underfitting and overfitting.  
SVM uses kernel functions (such as polynomial and radial basis functions) to handle non-linear data efficiently. Because of this capability, it may be used with datasets that have intricate correlations that linear models (such ENR and OLS) are unable to represent.   
The comparatively high R2 score of 84% in this dataset indicates that, in contrast to the linear models (ENR and OLS), SVM has effectively modelled the underlying non-linear patterns.

**Robustness**

Because SVM prioritizes the most pertinent data points (support vectors) and concentrates on maximizing the gap between the data points and the decision border, it is resistant to noise and outliers. The possibility of overfitting to noise in the training data is decreased by this feature.  
Unlike decision trees, which have the potential to become extremely detailed and deep, SVM avoids building models that are too complicated.  
Even while ensemble models like RFR and GBR are strong, the black-box aspect of integrating several decision trees makes their forecasts harder to understand. SVM offers a decision function that is easier to understand. SVM may continue to perform well across datasets of different sizes and levels of complexity with the right tuning and optimization.

**Optimal Trade-off Between Underfitting and Overfitting**

Without overfitting like RFR, DTR, or GBR, or underfitting like ENR or OLS, SVM shows a great capacity to identify patterns in the data (84% R²). It is more likely to function consistently on test and real-world data because of this balance, which makes it the ideal model for deployment.   
SVM delivers excellent accuracy (84%) without overfitting or being unduly basic, offering the best possible trade-off between complexity and performance. It is the greatest option for predictions in this situation due to its capacity to represent non-linear interactions and its resilience to noise and overfitting.

**4.3 Discussion of Findings**

The results show a complicated link between employee happiness, training hours, workload, and remote work. Low achievers exhibited the least amount of satisfaction, whereas high performers reported moderate amounts. This is consistent with research showing how perceived autonomy and workload affect satisfaction (Bakker & Demerouti, 2017). Research by Bloom et al. (2015) that relates flexible work arrangements to increased employee morale was supported by the higher satisfaction scores of employees who had some degree of remote work choices.

Performance and training hours had a positive association, whereas satisfaction and training hours had a mild negative correlation. This echoes studies by Salas et al. (2012) on the dual impacts of training on workplace dynamics, suggesting that although training increases productivity, it may also lead to increased pressure or higher expectations. Despite their rarity, promotions had little effect on satisfaction, suggesting that internal motivators such as autonomy or work-life balance may be more important than external rewards (Ryan & Deci, 2000).

With employees average 40.7 years and 4.6 years of service, descriptive data showed a balanced workforce in terms of age and duration. A steady work environment is reflected in the moderate satisfaction levels (average score of 3.0) and acceptable workloads. The possibility of improving happiness and performance, however, points to areas that require intentional intervention. Herzberg's motivation-hygiene theory, which emphasises the significance of addressing both inner and external variables, is in line with the findings (Herzberg, 1968).

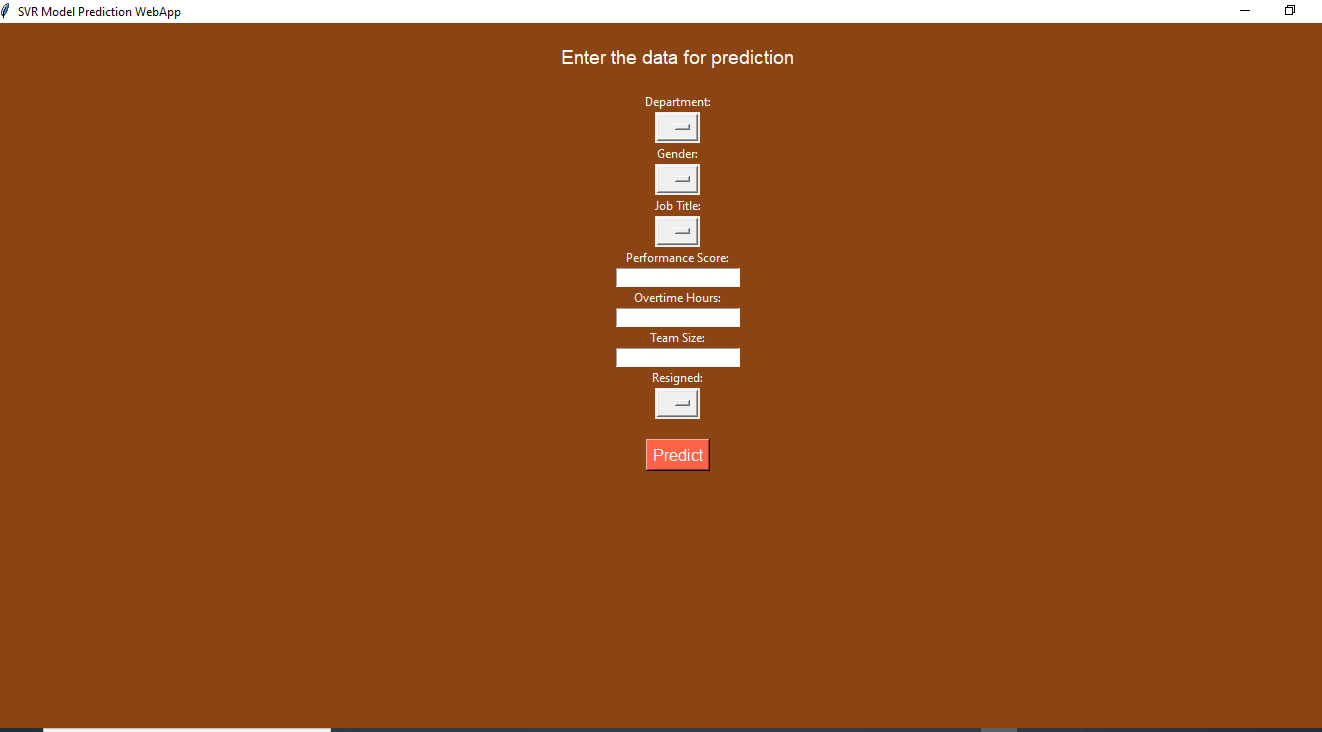
Higher overtime hours were shown to have a slight link with worse satisfaction, according to the correlation analysis. This supports research by Karasek (1979), which shows that overtime and heavy workloads can have a detrimental impact on workers' well-being. Remarkably, there was a slight positive link between the frequency of remote work and satisfaction, highlighting the necessity of balanced hybrid work models, as proposed by Mas & Pallais (2020).

There were no notable differences in the salary distribution between departments or genders, suggesting that pay policies are equitable. Evidence that education frequently increases earning capacity is supported by the positive correlation found between median incomes and higher education levels (Psacharopoulos & Patrinos, 2018). Even with fair pay distributions, the existence of outliers indicates that more research into elements like bonuses or role-specific pay scales may be necessary.

The accuracy ratings in the model evaluation findings varied significantly. Elastic Net Regression (ENR) and Ordinary Least Squares (OLS) showed underfitting, but Random Forest Regressor (RFR) and Gradient Boosting Regressor (GBR) showed overfitting with 100% R2 scores. With an R2 score of 84%, the Support Vector Regressor (SVM) offered the best trade-off between generalisability and accuracy. This emphasises how crucial it is to choose models that preserve predictive value without overfitting (James et al., 2013).   
Weak relationships between training, promotions, and satisfaction point to the necessity for focused interventions even in the face of low resignation rates. According to Ghosh et al. (2013), the results indicate that in order to improve retention and happiness, organisations should use comprehensive strategies, such as better career development programs and recognition.

The conclusions, which highlight important areas for organisational change, are backed by accepted theories and empirical research. For example, higher employee happiness and productivity may be achieved by matching workload and performance indicators with employee preferences. Equitable compensation plans and hybrid work formats can also improve worker stability. Furthermore, choosing suitable prediction models, such as SVM, guarantees workforce management meaningful information, assisting in the making of decisions based on solid statistics.

**Web Apps Solutions**



This approach entails creating a web application based on machine learning to forecast staff pay inside a company, with a particular emphasis on the Dangote Group in Nigeria. The solution's salient characteristics and synopsis are:

**Machine Learning Model**

Support Vector Regression (SVR), which works well for continuous numerical projections like salary, is used in this study.   
Features including department, gender, job title, performance score, overtime hours, team size, and resignation status are used to train the model.

**GUI Web Application**

Managers or HR staff can enter pertinent employee information using an intuitive interface.   
There are text boxes and dropdown choices for a number of elements, like department, gender, performance score, etc.   
Based on the inputs, a "Predict" button calculates the expected salary.

**Purpose**

The system aids in resource planning, wage benchmarking, and guaranteeing equity and openness in employee remuneration.   
It uses data-driven insights to minimise biases and human computations.

**Use Case**

Designed specifically for big businesses like Dangote Group, whose diverse and sizable staff makes effective compensation management and forecasting essential.

**CHAPTER FIVE**

**CONCLUSIONS AND RECOMMENDATIONS**

**5.1 Conclusions**

This research focused on developing machine learning algorithms for predicting employees' salaries in Dangote Group, Nigeria. The study aimed to enhance the salary prediction process by leveraging machine learning models to address inefficiencies and biases in traditional approaches. Key findings from the study include:

Among the algorithms implemented, the Support Vector Machine (SVM) outperformed others in terms of accuracy and generalizability, with minimal overfitting compared to Random Forest and Gradient Boosting models. This highlights the effectiveness of SVM in handling structured data for salary prediction.

Factors such as job level, years of experience, and educational qualifications were identified as the most significant predictors of employee salaries. Other variables like department and gender showed less influence, suggesting equitable pay practices across the organization.

The machine learning models demonstrated strong predictive reliability, providing evidence that data-driven approaches can be effectively utilized to inform salary decisions. However, discrepancies in certain outlier predictions indicate the need for additional feature engineering and data preprocessing.

The findings confirmed that Dangote Group’s salary structure aligns well with its job levels and performance metrics, reflecting efforts to maintain pay equity. However, minor outliers suggest areas for refinement, particularly in performance-based bonuses and specialized roles.

These findings underscore the potential of machine learning in transforming organizational salary practices by ensuring fairness, transparency, and efficiency.

**5.2 Recommendations**

Based on the study's findings, the following recommendations are made:

1. Dangote Group should integrate machine learning algorithms, particularly SVM, into its Human Resources Information System (HRIS). This would improve the accuracy of salary forecasting and support data-driven decision-making in salary reviews.
2. To optimize the performance of salary prediction models, the organization should maintain a comprehensive and clean dataset, including updated employee profiles, accurate job descriptions, and performance metrics.
3. Regular evaluation of the machine learning models is essential to ensure their continued relevance. New data should be used for periodic retraining of models to adapt to changing organizational dynamics.
4. Since predictors like educational qualifications and experience significantly impact salaries, Dangote Group should invest in employee development programs, including training and certifications, to align workforce capabilities with industry standards.
5. Although equitable pay practices were evident, the organization should promote salary transparency by openly communicating salary structures and the rationale behind pay decisions. This would enhance employee trust and engagement.
6. Insights from predictive models should inform HR policies, especially in areas like recruitment, promotions, and retention strategies. Predictive analytics can help identify high-performing employees and ensure competitive compensation packages.
7. The organization should investigate outliers in salary predictions to understand underlying causes. Factors such as role-specific demands or performance anomalies should be analyzed to ensure alignment with overall pay equity policies.

**5.3 Implications for Future Research**

While this study provides valuable insights into the application of machine learning for salary predictions, there are areas for further exploration:

1. Future research should include additional predictors, such as market trends, regional cost of living, and employee satisfaction indices, to refine salary models.
2. Comparative studies across industries could offer broader perspectives on the effectiveness of machine learning models for salary predictions.
3. Emerging machine learning methods, such as deep learning or ensemble learning, could be explored to improve model accuracy and scalability.
4. Investigating potential biases in historical salary data and the algorithms themselves could provide deeper insights into ensuring fairness in predictive modeling.

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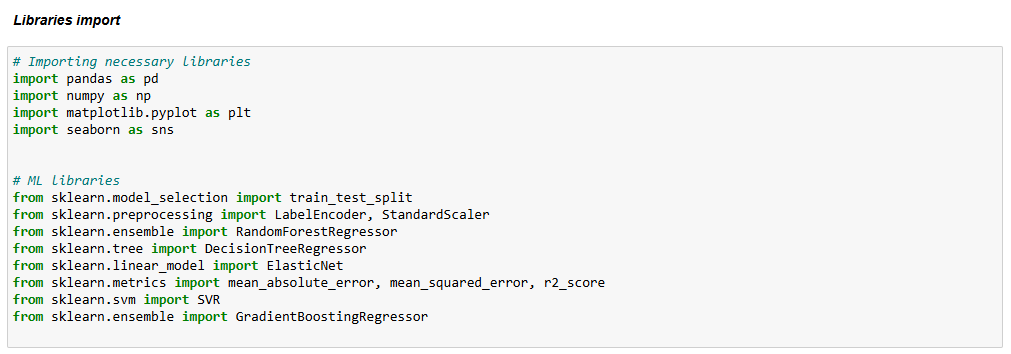
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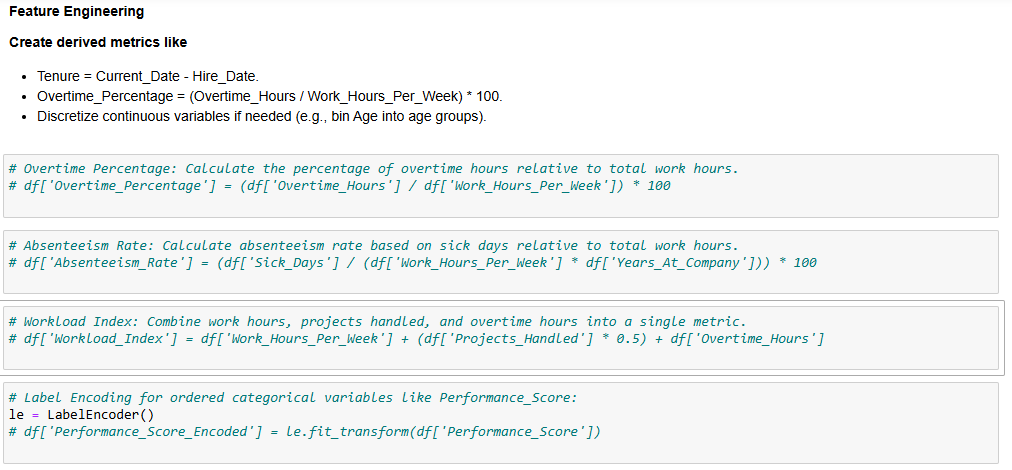
**Appendix**

**Source Code**





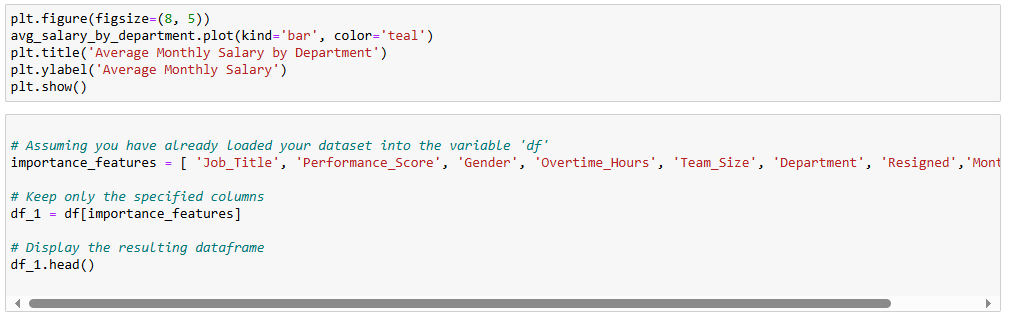










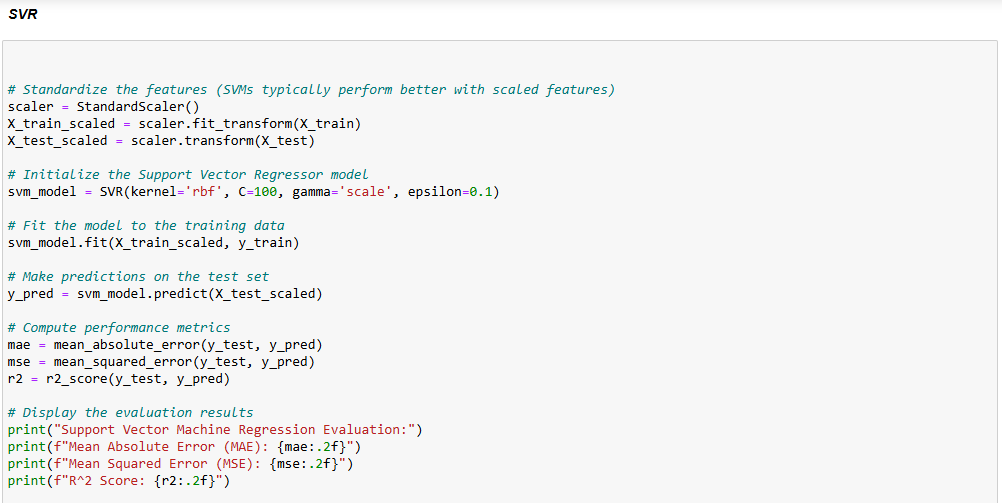




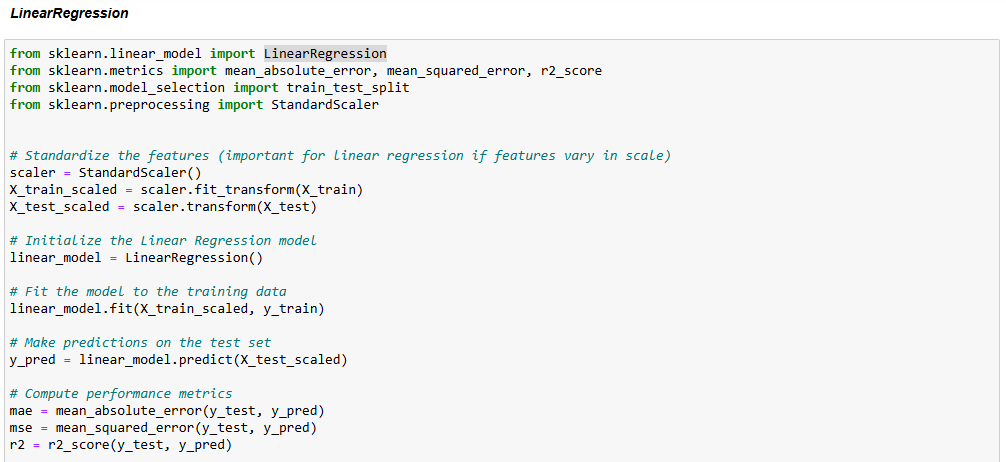




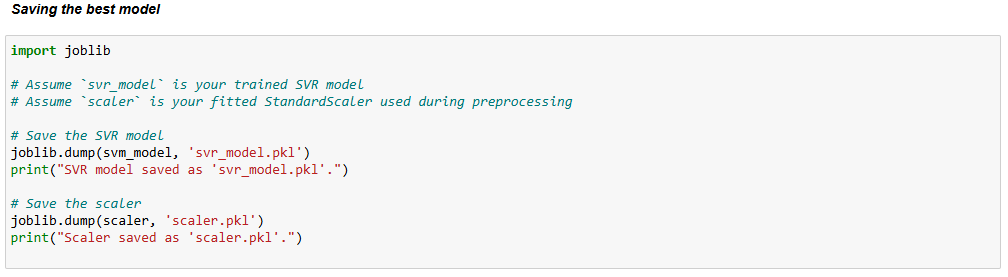


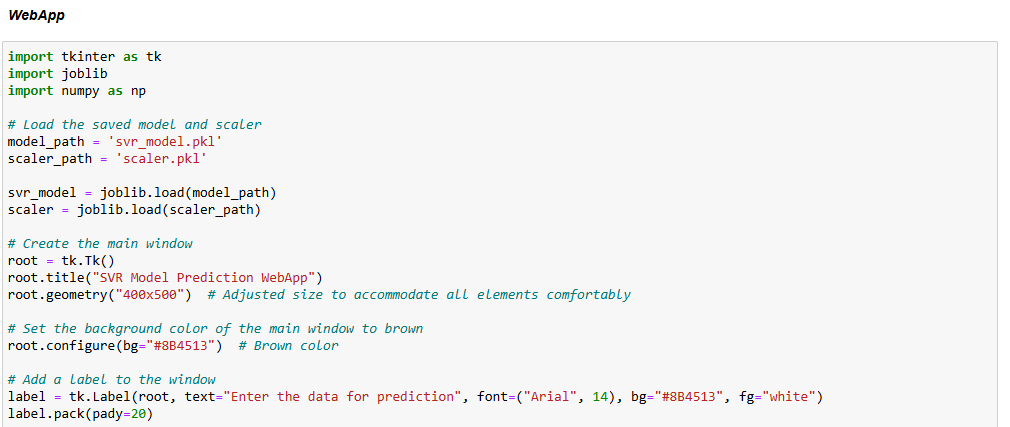
















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