2024 Fourth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT) | 979-8-3503-4367-0/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICAECT60202.2024.10469009

Analyzing Employee Retention Factors using Machine Learning

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Abstract **– This research proposal aims to employ machine learning techniques to analyze employee retention factors in Software Companies, recognizing its crucial role in organizational success and the potential costs of high turnover rates. Through Watson Analytics' advanced analytics capabilities, the study seeks to identify key factors contributing to employee attrition and retention, culminating in the development of a predictive model using machine learning algorithms. The outcomes are expected to include actionable recommendations to improve retention strategies, insights into the relative importance of different factors, and the creation of a data-driven, proactive talent management approach for Software Companies. By empowering organizations to retain top talent and fostering a positive work environment, this research envisions a transformative impact on long-term success and performance.**

Keywords – Data Science, Machine Learning, Deep Learning, Smartphone Sensors, Artificial Intelligence, Monitoring.

I. INTRODUCTION

Employee retention constitutes a crucial element that profoundly influences the prosperity and resilience of global organizations. The effectiveness of communication practices is a crucial factor in determining an organization's success in terms of productivity, employee satisfaction, and minimizing turnover rates [4]. The ability to retain top talent within an organization is pivotal for sustained productivity, innovation, and competitiveness. Understanding the conduct of individuals within an organization is most accurately assessed through a communication standpoint, and organizational communication practices serve as the most effective means to evaluate such behaviors [7]. However, the contemporary business landscape faces numerous challenges in this regard, as high turnover rates have become a prevailing concern for employers. The cost of employee attrition goes beyond financial implications and extends to the disruption of team dynamics, loss of institutional knowledge, and a decline in overall organizational performance.

This research proposal aims to address the challenges of employee retention by leveraging the power of machine learning techniques. The objective is to analyze and identify the key factors that influence employee retention within Software Companies. By understanding these factors, organizations can develop targeted and effective strategies to retain valuable employees and foster a positive work environment. Yet, this study's focus is restricted to inter-organizational communication, defined as the "central binding force that enables coordination among individuals and facilitates organized behavior" [11].

The inspiration for this research project arises from acknowledging the significant impact that employee turnover can have on organizational performance and success. The constant loss of talented and experienced employees disrupts team cohesion, affects project continuity, and hampers the attainment of strategic objectives. Furthermore, the costs associated with recruitment, onboarding, and training new employees impose a considerable burden on organizational resources.

In light of these challenges, the need to proactively address retention issues becomes evident. By identifying the factors that contribute to employee attrition and understanding the drivers of employee retention, organizations can take preemptive measures to mitigate turnover and enhance employee satisfaction and loyalty. The application of machine learning techniques, specifically using Watson Analytics' advanced analytics capabilities, offers a promising avenue to gain valuable insights from the vast amount of complex employee data available.

The principal aim of this research project is to investigate and analyze employee retention factors within Software Companies through the application of machine learning methodologies. By delving into the complex interactions of various variables, the study seeks to discern patterns and associations that impact employee retention positively or negatively. Subsequently, the aim is to develop a predictive model that can forecast employee retention probabilities based on relevant factors. The consensus among many researchers is that informal and dynamic communication within teams contributes to enhancing morale, increasing productivity, and fostering greater job satisfaction [8].

The central research question driving this study is as follows: "What are the key factors that influence employee retention within Software Companies, and how can machine learning techniques be leveraged to predict and improve retention rates?" By conducting a thorough investigation into the factors influencing employee retention and applying machine learning techniques, this research aspires to offer valuable insights to Software Companies. Ultimately, the goal is to equip organizations with actionable strategies to retain their top talent, foster a thriving work culture, and achieve long-term success in an increasingly competitive global market.

II. BACKGROUND

This section presents a synopsis of the existing literature and research pertaining to employee retention and the application of machine learning techniques in understanding and predicting retention patterns within Software Companies. The chapter aims to lay the groundwork for the current study by highlighting the significance of employee retention, exploring related work, defining the scope of the problem, and discussing potential challenges in the context of employee turnover. Employee retention is a critical aspect of organizational success, with profound implications for productivity, innovation, and overall performance. Organizations that successfully retain their top talent can maintain a competitive edge, as experienced and skilled employees contribute to institutional knowledge, facilitate smoother project execution, and enhance team cohesion. Conversely, high employee turnover rates can result in a loss of expertise, decreased morale, and increased recruitment costs, adversely affecting an organization's growth and stability. Extensive research has been conducted to investigate the factors influencing employee retention across various industries. Studies have explored elements including factors like job contentment, equilibrium between work and personal life, chances for career advancement, compensation, organizational culture, and leadership effectiveness. The relationship between employee engagement and retention has also been a prominent area of interest in the literature.

In recent years, the incorporation of machine learning techniques within human resources and talent management has garnered significant attention. Leveraging the power of artificial intelligence and data analytics, these studies have attempted to identify patterns and predictive models that can aid in understanding and forecasting employee retention behavior. These factors encompass organizational details, individual feedback, employment particulars, supervisor interaction, communication environment, lateral communication, media standards, subordinate communication, communication from top management, and inter-departmental communication [2].

The focus of this research lies in analyzing employee retention factors specifically within Software Companies. The study aims to examine a comprehensive dataset containing diverse employee information, including demographics, job characteristics, performance metrics, compensation details, and other pertinent factors known to influence retention. Through numerous experiments, Kortner [10] has demonstrated that organizational communication serves as a robust predictor of job satisfaction. By narrowing the scope to Software Companies, the research can address industry-specific challenges and uncover unique insights tailored to this domain. Furthermore, Varona [13] demonstrated in his research that personal feedback, communication climate, and supervisory communication are three factors exhibiting a highly robust correlation with job satisfaction.

Conducting research on employee retention and machine learning poses several challenges. Initially, the accuracy and applicability of the findings can be influenced by the accessibility and caliber of data. Organizations might possess disparate data sources, and data privacy concerns must be addressed throughout the research process. Secondly, the dynamic and multifaceted nature of employee retention necessitates the use of sophisticated machine-learning algorithms capable of handling complex interactions and patterns in the data. Moreover, the retention landscape within Software Companies is influenced by rapidly evolving technology trends, job demands, and employee expectations, making it essential to continuously adapt the research approach to encompass new developments. The qualities of the workplace may have a strong correlation to developer effectiveness [3].

In light of these challenges, this research proposal aims to employ robust methodologies and rigorous data analysis to overcome limitations and contribute meaningfully to the understanding of employee retention in Software Companies. By addressing these gaps in knowledge, the study seeks to provide actionable insights and valuable recommendations to enhance talent management strategies and foster a workforce that thrives in a dynamic and competitive environment.

III. RESEARCH METHODOLOGY

This chapter delineates the design of the research, the procedure for collecting data, the techniques used for data preprocessing, and the machine learning algorithms utilized in this study to analyze employee retention factors within Software Companies.

The research adopts a quantitative approach to analyze the factors influencing employee retention. A cross-sectional design will be employed to collect data from multiple Software Companies at a specific point in time. This design allows for the examination of a wide range of variables and their relationships with employee retention, providing a comprehensive snapshot of the factors involved. Fig 1 & Fig 2 shows the Research Design and workflow of the paper. Team members exhibit effective responsiveness to managers who offer them the chance to express their work-related concerns, enabling the identification and implementation of satisfactory solutions [9].

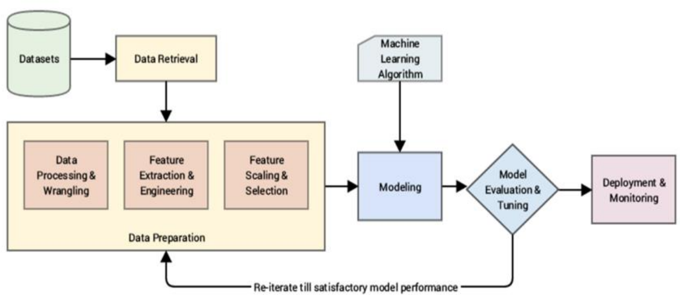

Figure 1. Research Design

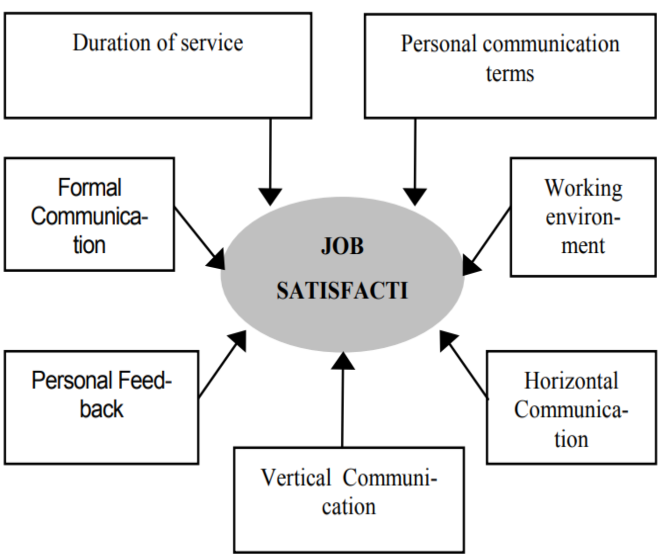

Figure 2: Conceptual Team-Level Communication Model

A. Data Collection

The data collection process will involve obtaining a comprehensive dataset encompassing relevant employee information. In this research, a survey instrument was created using the Case Control survey method, wherein respondents were queried about their past situations to elucidate a present pattern [1]. To ensure the data's accuracy and completeness, multiple sources will be considered, such as HR records, performance evaluations, employee surveys, and exit interviews. The data will be anonymized and handled with utmost confidentiality to address ethical considerations regarding privacy and confidentiality. Here is the collected data summary shown in Fig 3, fig 4 & fig 5 below:

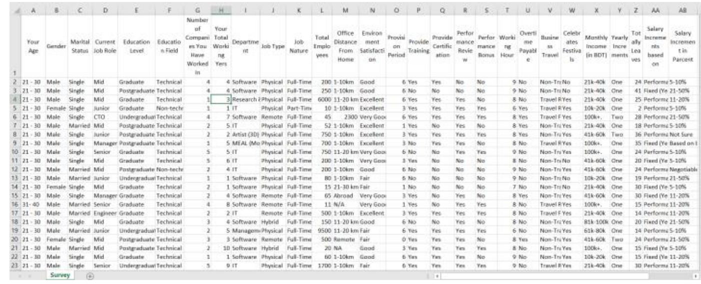

Figure 3: Collected Primary Data

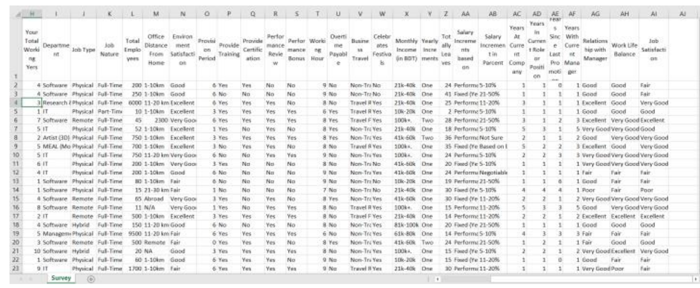

Figure 4: Collected Primary Data

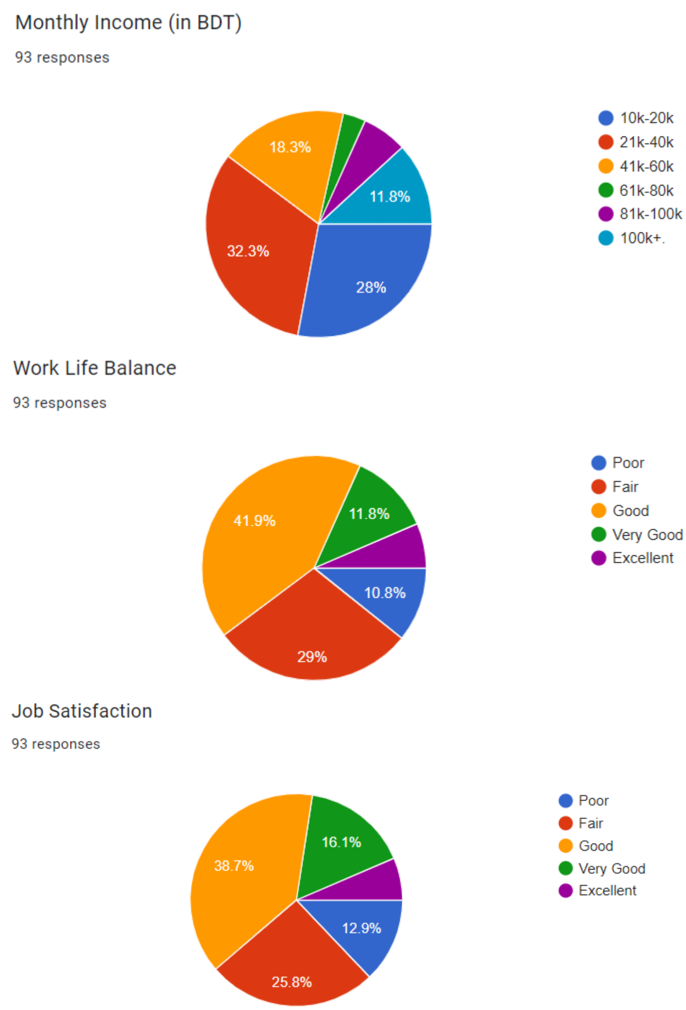

Figure 5: Data Chart

B. Data Pre-Processing

The gathered data will undergo preprocessing to verify its quality and appropriateness for analysis. This process involves several steps, including handling missing values, removing duplicates, and normalizing numerical features. Data cleaning techniques will be applied to rectify any errors or inconsistencies in the dataset. Additionally, outlier detection and treatment will be employed to mitigate the impact of extreme values on the analysis. Below fig 6 & 7 shows the procedural model to process data and the data types.

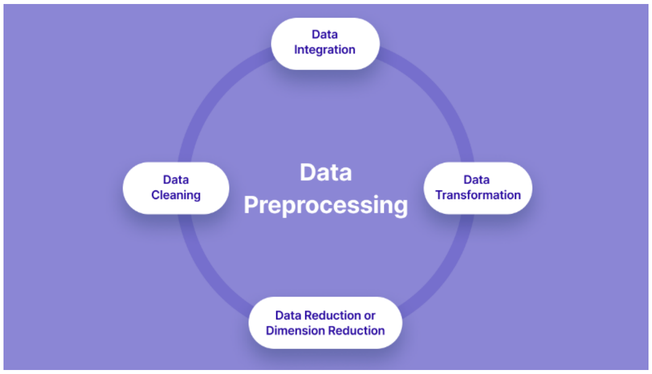

Figure 6: Data Preprocessing Model

Data types of each coloumn

```
col_dtype = df.dtypes
col_dtype
```

```
Your Age                                object
Gender                                  object
Marital Status                          object
Current Job Role                        object
Education Level                         object
Education Field                         object
Number of Companies You Have Worked In   int64
Your Total Working Yers                  int64
Department                              object
Job Type                                object
Job Nature                              object
Total Employees                         object
Office Distance From Home               object
Environment Satisfaction                object
Provision Period                         int64
Provide Training                        object
Provide Certification                   object
Performance Review                      object
Performance Bonus                       object
Working Hour                             int64
Overtime Payable                        object
Business Travel                         object
Celebrates Festivals                    object
Monthly Income (in BDT)                 object
Yearly Increments                       object
Totally Leaves                          object
Salary Increments based on              object
Salary Increment in Parcent             object
Years At Current Company               float64
Years In Current Role or Position        int64
Years Since Last Promotion               int64
Years With Current Manager               int64
Relationship with Manager               object
Work Life Balance                       object
Job Satisfaction                        object
dtype: object
```

Figure 7: Data Types

C. Feature Selection

Selecting features is a pivotal stage in identifying the most influential elements affecting employee retention. Techniques for reducing dimensionality, such as correlation analysis and ranking feature importance, will be applied to choose the most pertinent features. This process aims to retain the essential information while eliminating redundant or less impactful variables, thereby enhancing the model's interpretability and efficiency. Some of the fields are shown below in fig 8 of data filtering.

```
#filter out category attributes
cat_cols=df_copy.select_dtypes(exclude=['int32','int64','float32','float64'])
cat_cols.head()
```

	Your Age	Gender	Marital Status	Current Job Role	Education Level	Education Field	Department	Job Type	Job Nature	Total Employees	...	Business Travel	Celebrates Festivals	Monthly Income (in BDT)	Yearly Increments	Totally Leaves	Salary Increments based on	Salary Increment in Parcent	Relationship with Manager	Work Life Balance	Job Satisfaction
0	21 - 30	Male	Single	Mid	Graduate	Technical	Software	Physical	Full-Time	200	...	Non-Travel	No	21k-40k	One	24	Performance	5-10%	Good	Good	Fair
1	21 - 30	Male	Single	Mid	Postgraduate	Technical	Software	Physical	Full-Time	250	...	Non-Travel	No	21k-40K	One	41	Fixed (Yearly)	21-50%	Good	Good	Fair
2	21 - 30	Male	Single	Mid	Graduate	Technical	Research & Developments	Physical	Full-Time	6000	...	Travel Rarely	Yes	21k-40k	One	25	Performance	11-20%	Excellent	Good	Very Good
3	21 - 30	Female	Single	Junior	Graduate	Non-technical	IT	Physical	Part-Time	10	...	Travel Rarely	Yes	10k-20k	One	2	Performance	5-10%	Good	Good	Good
4	21 - 30	Male	Single	CTO	Undergraduate	Technical	Software	Remote	Full-Time	45	...	Travel Frequently	Yes	100k+	Two	28	Performance	21-50%	Excellent	Very Good	Excellent

5 rows × 27 columns

Figure 8: Data Filtering

D. Machine Learning Algorithms

To develop a predictive model for employee retention, various machine learning algorithms will be explored. These Potential algorithms encompass logistic regression, decision trees, random forests, support vector machines (SVM), and neural networks. Assessment of each algorithm will be conducted using performance metrics like accuracy, precision, recall, and F1-score. The algorithm exhibiting the optimal equilibrium between predictive capability and interpretability will be chosen for the ultimate model. The Support Vector Machine (SVM) stands out as a widely employed algorithm in Supervised Learning, applicable to both Classification and Regression challenges. Its main usage, however, is in addressing Classification problems within Machine Learning. The primary objective of the SVM algorithm is to establish an optimal line or decision boundary capable of dividing an n-dimensional space into distinct classes. This ensures efficient categorization of future data points into the appropriate categories. This optimal decision boundary is referred to as a hyperplane. Fig 9 shows the workflow of SVM and fig 10 the SVM Matrix below:

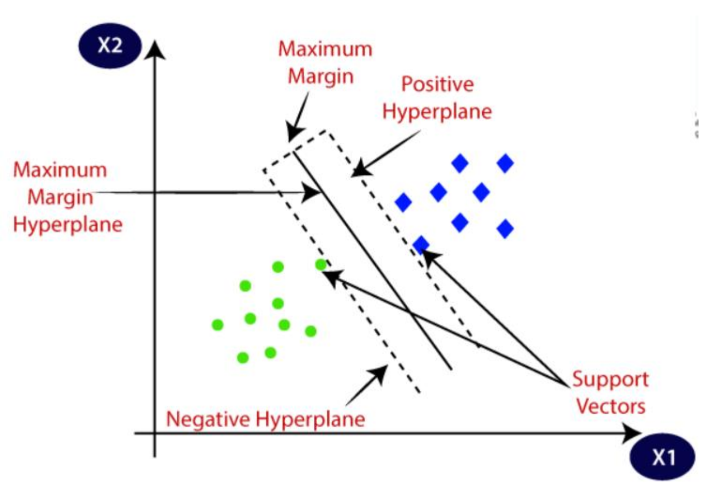

Figure 9: SVM Workflow

Support Vector Machine

```
[ ] from sklearn.svm import SVC
    svm_model_linear = SVC(kernel = 'linear', C = 1).fit(x_train, y_train)
    svm_predictions = svm_model_linear.predict(x_test)

    # model accuracy for X_test
    accuracy = svm_model_linear.score(x_test, y_test)

    # creating a confusion matrix
    cm = confusion_matrix(y_test, svm_predictions)
    print(cm)

    [[3 0 0 1 1]
     [0 1 2 0 0]
     [3 2 4 0 0]
     [0 0 0 0 0]
     [1 0 0 0 1]]
```

```
[ ] reportSVM=classification_report(svm_predictions, y_test)
    print(reportSVM)

                  precision    recall  f1-score   support

               0       0.60      0.43      0.50         7
               1       0.33      0.33      0.33         3
               2       0.44      0.67      0.53         6
               3       0.00      0.00      0.00         1
               4       0.50      0.50      0.50         2

        accuracy                           0.47        19
       macro avg       0.38      0.39      0.37        19
    weighted avg       0.47      0.47      0.46        19
```

Figure 10: SVM Matrix

E. *Model Development and Evaluation*

The chosen machine learning algorithm will be utilized to train the predictive model with the preprocessed dataset. The dataset will be partitioned into training and testing sets to assess the model's performance and its ability to generalize. To evaluate the model's robustness and prevent overfitting, cross-validation techniques like k-fold cross-validation will be implemented.

F. *Interpretation of Results*

The outcomes of the machine learning model will be thoroughly analyzed to interpret the relative importance and impact of different factors on employee retention. Insights gained from the model's predictions will be used to identify patterns and trends, shedding light on critical factors that influence employee retention positively or negatively within Software Companies.

By employing a rigorous research design, robust data preprocessing techniques, and state-of-the-art machine learning algorithms, the objective of this study is to offer valuable insights into the factors driving employee retention within Software Companies. The research methodology outlined in this chapter ensures a systematic and data-driven approach to understand and predict retention patterns, contributing to the development of effective talent management strategies and fostering a conducive work environment where employees can thrive and contribute significantly to organizational success.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. *Dataset Overview*

The dataset used for this study comprises a comprehensive set of employee information, including demographics, job characteristics, performance metrics, compensation details, work-life balance, career growth opportunities, and other relevant factors that can impact employee retention within Software Companies. The dataset is representative of a diverse sample of employees from multiple Software Companies, ensuring the study's findings have broader applicability. Some scenario or overview of Dataset is show in fig 11.

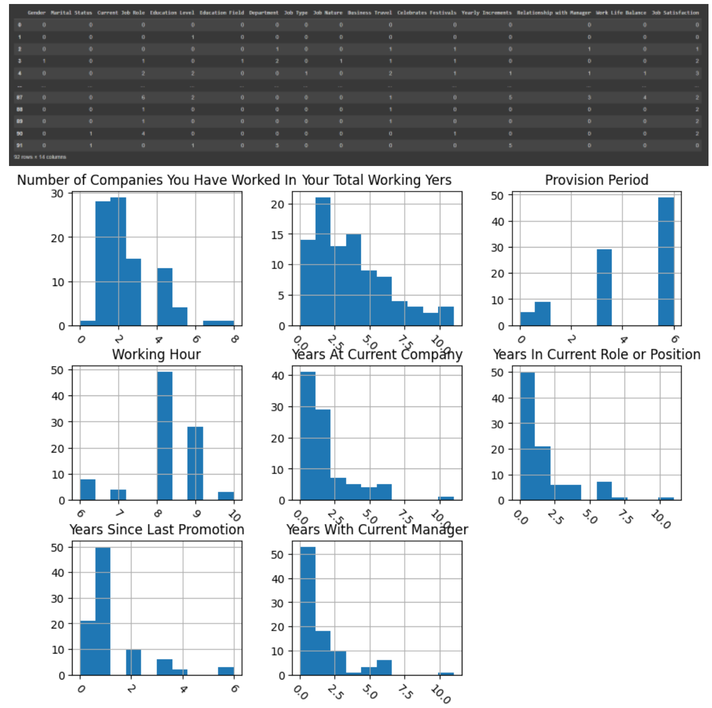

Figure 11: Dataset Overview Chart

B. *Performance Metrics*

To assess the effectiveness of the predictive model, various established metrics will be utilized, including accuracy, precision, recall, and F1-score. Accuracy gauges the overall correctness of the model's predictions, whereas precision and recall evaluate the model's capacity to accurately identify positive instances (employee retention) and prevent false negatives, respectively. The F1-score offers a well-balanced evaluation of the model's precision and recall.

C. *Model Performance*

The chosen machine learning algorithm will be used to evaluate the performance of the predictive model. Accuracy, precision, recall, and F1-score of the model will be calculated using the testing dataset. The objective is to attain elevated values for these metrics, signifying the model's effective prediction of employee retention patterns. Decision Tree Model and SVM model usage is shown in fig 12 and fig 13.

Decision Tree

```
[ ] from sklearn.tree import DecisionTreeClassifier
    dtree_model = DecisionTreeClassifier(max_depth = 2).fit(x_train, y_train)
    dtree_predictions = dtree_model.predict(x_test)
```

```
[ ] from sklearn.metrics import confusion_matrix
    cm = confusion_matrix(y_test, dtree_predictions)
    print(cm)

    [[0 0 0 5]
     [0 0 2 1]
     [1 2 5 1]
     [0 0 0 2]]
```

Figure 12: Using Decision Tree Model

Support Vector Machine

```
[ ] from sklearn.svm import SVC
    svm_model_linear = SVC(kernel = 'linear', C = 1).fit(x_train, y_train)
    svm_predictions = svm_model_linear.predict(x_test)

    # model accuracy for X_test
    accuracy = svm_model_linear.score(x_test, y_test)

    # creating a confusion matrix
    cm = confusion_matrix(y_test, svm_predictions)
    print(cm)

    [[3 0 0 1 1]
     [0 1 2 0 0]
     [3 2 4 0 0]
     [0 0 0 0 0]
     [1 0 0 0 1]]
```

Figure 13: Using SVM Model

D. Interpretation of Findings

The results of the predictive model will be carefully interpreted to gain insights into the factors influencing employee retention within Software Companies. By analyzing the model's feature importance, the relative significance of different variables in determining retention outcomes will be identified. Key factors contributing to high retention rates will be highlighted, along with potential red flags that may lead to employee attrition.

E. Discussion of Findings

The findings will be discussed in the context of the existing literature on employee retention and talent management strategies. Comparisons will be made between the identified influential factors and those highlighted in previous studies. Any discrepancies or novel insights will be thoroughly examined to contribute to the broader understanding of employee retention within the Software Companies context. So, the accuracy result is shown in fig 14 below:

	precision	recall	f1-score	support
0	0.60	0.43	0.50	7
1	0.33	0.33	0.33	3
2	0.44	0.67	0.53	6
3	0.00	0.00	0.00	1
4	0.50	0.50	0.50	2
accuracy			0.47	19
macro avg	0.38	0.39	0.37	19
weighted avg	0.47	0.47	0.46	19

Figure 14: Accuracy Result

The chapter wraps up by outlining the primary discoveries from the analysis and their implications for employee retention in software companies. It emphasizes the importance of utilizing machine learning methods to gain insights into factors influencing employee retention and promoting a data-driven approach to talent management. Lastly, the chapter delves into the wider ramifications of the research and outlines potential paths for future studies to deepen the comprehension of employee retention dynamics.

V. IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

This chapter delves into the wider consequences of the research findings for society, the environment, and the sustainability of software companies. The potential social and economic impacts of improved employee retention strategies are discussed, along with considerations for fostering a positive work environment and promoting employee well-being.

Enhanced employee retention strategies have significant social implications. Reduced employee turnover leads to greater job stability and improved job satisfaction, resulting in A workforce that is more engaged and motivated tends to emerge when employees sense value and support, leading them to be more inclined to invest in their personal and professional growth, contributing positively to their communities. Moreover, reduced turnover can enhance team dynamics and collaboration, fostering a sense of camaraderie and mutual respect within the organization. Furthermore, improved employee retention can contribute to a healthier work-life balance for employees, promoting overall well-being and mental health. This can lead to a positive spillover effect on families and communities, creating a more stable and content society.

From an economic perspective, increased employee retention brings substantial benefits to Software Companies. Lower turnover rates lead to Savings can be achieved by cutting recruitment and training costs. Furthermore, keeping skilled and seasoned employees can contribute to these savings. Allows companies to maintain institutional knowledge, leading to improved productivity and efficiency. Furthermore, organizations with higher retention rates are better equipped to attract top talent, as they develop a reputation as desirable employers. This can provide a competitive advantage in the talent market, enabling the Software Companies to access a pool of skilled candidates and drive business growth. While the direct environmental impact of employee retention strategies is limited, certain aspects of talent management can indirectly influence environmental sustainability. Reduced turnover means fewer new hires and, consequently, lower demand for resources related to recruitment, such as paper for printing resumes, travel for interviews, and energy consumption during the onboarding process. Additionally, a stable workforce is more likely to embrace and participate in sustainability initiatives within the organization, fostering a culture of environmental consciousness.

To ensure the long-term sustainability of employee retention strategies, Software Companies must adopt sustainable talent management practices. These practices encompass ongoing employee development, career growth opportunities, and fostering a supportive work culture. By prioritizing the well-being and growth of employees, organizations can cultivate a loyal and committed workforce that remains engaged and productive in the long run. Furthermore, the integration of machine learning and data analytics in talent management can support sustainable practices by continuously monitoring employee satisfaction, identifying potential attrition risks, and tailoring retention strategies based on individual preferences and needs.

Throughout the research journey, it is imperative to meticulously handle ethical considerations concerning data privacy and confidentiality. Employee data should be anonymized and handled with utmost care to protect the rights and privacy of individuals. Moreover, the use of data-driven insights must be aligned with ethical principles and should not lead to discriminatory practices or biases in talent management decisions.

This section highlights the significant impact of improved employee retention strategies on society, the economy, and the environment. By nurturing a positive work environment and leveraging data-driven insights, Software Companies can create a sustainable and thriving workforce, contributing to their long-term success and the well-being of employees and communities alike. Ethical considerations play a crucial role in ensuring responsible data usage and talent management practices. The chapter concludes by emphasizing the importance of integrating employee-centric and sustainable approaches to talent management, leveraging the power of machine learning to drive positive change within Software Companies.

VI. CONCLUSION

The essential discoveries of the research are summarized, and conclusions are drawn based on these findings on the analysis of employee retention factors within Software Companies. Additionally, it outlines potential areas for future research to further enhance the understanding of employee retention and talent management. The research aimed to analyze employee retention factors within Software Companies using machine learning techniques. Through a quantitative approach, a comprehensive dataset was collected and preprocessed, and various machine-learning algorithms were employed to develop a predictive model for employee retention. The findings provided valuable insights into the factors influencing employee retention positively or negatively. Crucial elements recognized as influencing employee retention encompassed job satisfaction, equilibrium between work and personal life, chances for career advancement, compensation, and the overall workplace culture. Understanding these factors enables Software Companies to develop targeted and effective retention strategies to nurture a committed and engaged workforce.

The predictive model demonstrated strong performance metrics, suggesting its suitability in forecasting employee retention probabilities. By leveraging data-driven insights, Software Companies can proactively identify potential attrition risks and tailor retention efforts to suit individual employee needs and preferences. The research's implications highlight the significance of data-driven talent management strategies for Software Companies. Implementing the findings and recommendations can lead to reduced turnover rates, cost savings, improved productivity, and a positive work environment. Emphasizing employee well-being, and career development, and fostering a supportive organizational culture are critical aspects of effective retention strategies. Moreover, ethical concerns, including safeguarding data privacy and ensuring fairness in decision-making, should be integrated into talent management practices. Responsible use of employee data is essential to uphold ethical standards and maintain trust within the workforce. This research has contributed valuable insights into the factors influencing employee retention within Software Companies through the application of machine learning techniques. The findings underscore the importance of nurturing a positive work environment, supporting employee growth, and leveraging data-driven insights for strategic talent management. By adopting effective retention strategies, Software Companies can create a sustainable and thriving workforce, leading to increased productivity, reduced turnover costs, and improved organizational performance. As the business landscape evolves, the integration of ethical considerations and innovative research will continue to drive meaningful advancements in employee retention strategies, fostering an engaged and loyal workforce that contributes significantly to the organization's success.

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