Predicting Employee Attrition using Explainable Machine Learning Algorithm

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APPROVAL

This thesis titled on "**Predicting Employee Attrition using Explainable Machine Learning Algorithm**", submitted by **Tazim Sultana (ID: 191-35-405)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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I announce hereby that I am rendering this study document under Dr. Md. Fazla Elahe, Associate Professor, Department of Software Engineering, Daffodil International University. I therefore, state that this work or any portion of it was not proposed here therefore for Bachelor's degree or any graduation.

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Most importantly, my pillars of emotional strength - my friends: Sajid, Fahad, Farhana and Badshah this couldn’t have been done without your unconditional love, unwavering patience and support.

Abstract

Attrition is one of the most critical problems with employees that our society faces today. The most significant loss for a business is when employees leave. Almost every business today gives careful thought to how to keep their employees. But they can't figure out why people leave their jobs. Employee attrition is the loss of employees that happens naturally in a company because of things that can't be changed. Attrition, how hard it is for the organizers to keep workers, and suggestions for keeping them. Attrition is the gradual loss of staff members because of things that can't be helped, like people quitting for personal or professional reasons. When employees are let go, an organization loses a lot of money. Most of the time, employers can't do anything about the fact that more people are leaving their jobs than are being hired. The Society for Human Resource Management (SHRM) says that the average cost to hire a new employee is USD 4,129, based on recent data. In 2021, the rate of people leaving was expected to be 57.3%. A research study needs to be done to determine why employees leave and to develop a way to predict employee turnover (Raza et al., 2022). This study aims to look at organizational factors that lead to employees leaving and predict the rate of employees leaving using machine learning techniques that are easy to understand. The other goal of this study is to find out what makes employees leave the most. In the past few years, researchers have looked at different machine-learning algorithms and found out why they work the way they do. Our study found that monthly income, hourly wage, job level, job satisfaction, and age are why employees leave their jobs (Raza et al., 2022). Our suggested strategy and research results assist organizations in identifying the actual reasons why employees leave their jobs. A company can also stop employees from leaving by addressing why they leave. Many workers also quit their jobs for various hidden reasons, such as not feeling secure in their jobs, not being able to move up in their careers, wanting to try something new, wanting to make more money, having problems with their bosses, or other personal reasons. This study assists in understanding the challenges employers face in retaining employees and the factors contributing to employee attrition.

Key-Word: Machine learning, explainable machine learning algorithm, employee, attrition, LIME, SHAP, organization, SVM, LR are all important word.

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Chapter-1: Introduction

Attrition is a natural process when people quit their jobs and aren't quickly replaced, like when they retire or leave for personal reasons. Attrition can also mean a client base is shrinking because customers are leaving and not as many new ones are coming in. Employee turnover is caused by more than one thing. They are made up of:

1. Pay and/or benefits that aren't enough
2. Not having a chance
3. Unfavorable working circumstances
4. an insufficient balance between work and life
5. Being sick and dying
6. Retirement
7. Moving away

When a skilled and adaptable employee leaves the company for any reason, a hole is left, and the company feels empty. It makes it hard for the people who work in human resources to close the gap created. When an employee or talented person leaves, the business loses a lot of money because it costs a lot more to hire them, train them, and pay for other things that help them get better at their jobs. One example will be if a worker quits in the middle of a project. In this case, they need to hire someone else to fill the spot. The new employee needs to be trained and know what the project is about and why it's essential. This would change how the other person on the team felt. The issues of staff attrition are discussed in this article, along with some recommendations for employee retention. The number of employees who leave a company is called its "attrition rate"(Raza et al., 2022). By keeping an eye on the staff turnover rate, we can figure out what needs to be done to stop it and what factors are to blame. To figure out the attrition rate, you divide the number of people who left the company by the average number of people who worked there during a specific period. Using the attrition rate, we can see how the company has changed over time.

1.1: Background

According to statistics on employee turnover, one-third of new hires leave the company after six months. The Job Openings and Labor Turnover Survey (JOLTS) says that between 3 and 4.5 million people in the United States quit their jobs every month. In 2021, 57.3% of employees left their jobs, according to the Bureau of Labor Statistics (Raza et al., 2022). The report also says that the number of people leaving their jobs is around 19% in many industries. SHRM says that for new hires, rent costs $4129 per month. That is the best when a company keeps 90% of its employees. As you can see from what has been said, the rate of employee reduction should be less than 10%. A report on a workplace survey found that 94% of people said they would stay with a company longer if it put money into their education.

Machine learning is a branch of artificial intelligence that looks at how machines can act like intelligent people. Artificial Intelligence (AI) looks into complicated problems by doing tasks similar to how people solve problems. Machine learning is one way AI is used. The evaluation data is a subset of the training data used to measure how well the machine-learning model works with new data. The end of the model can be used with different data sets. Machine learning techniques aim to get more accurate results than humans can. Machine learning models are used to decide what to do. Every day, technology finds more and more ways to use machine learning.

The main applications of machine learning cover a broader range of real-world domains Machine learning techniques are used to solve many common problems in the real world, such as health care, data security, image recognition, text classification, traffic prediction, speech recognition, weather prediction, social, analysis, e-commerce, agriculture, and more (Raza et al., 2022). There are several ways that machine learning can be used in the real world to save businesses time and money.

You could save money that could have a significant effect on the future of your business. To forecast employee attrition, machine learning models are used. Explainability in machine learning is the ability to explain what happens in your model from input to output. It removes the "black box" problem and makes models clear. I used explicit machine learning with XML models to predict employee turnover.

XAI is a term for methods that help human experts understand solutions made by AI. This is called explainable AI (XAI) in a more formal sense and applies to all types of AI. Consider the following situation: You are making a model for a software company.

That predicts how many employees will leave. You can probably figure out what you're doing and understand the model. But there is no way to explain it. When you look into the data and factors that led to the results, it will become clear why. The goal of being able to explain. It is to understand which features make up the model, how they relate to the model's predictions, and why.

In Explainable Artificial Intelligence, you can use methods like LIME (Local Interpretable Model Agnostic Explanations), SHAP (Shapley Values), Deep Taylor Decomposition (DTD), XGNN (Explainable Graph Neural Networks), TCAV (Testing with Concept Activation Vectors), and others. I used SHAP in this research study (Fritz-Morgenthal et al., 2022).

1.2Why was the research done

The main goals of this thesis are to find the main reason why employees quit and figure out how much of that reason is really to blame. Even though a lot has been learned about employee turnover, some questions still need to be answered. Before, machine learning algorithms were used to predict employee turnover, but they worked in a way that was hard to understand, like a "black box" technique. I'll work with you to create an updated machine-learning model that is easy to understand and can answer any question from a person. An explainable machine learning model called Local Interpretable Model-Agnostic Explanations (LIME) will be used to clarify why employees leave. When the attrition factor is understood well, it will be possible to treat employees in a way that strengthens the relationship between the business and its workers. Damage can be kept to a minimum. Additionally, employees will get a work atmosphere that respects their legal rights. With any luck, this research will show the company what steps to take in the future to help their business.

1.3: Problem with research

This thesis aims to predict employee turnover rates by using the idea that AI algorithms should be able to be explained. Using the recently made SHAP Python library to apply a dataset of employees to a SHAP model, get outputs, and figure out what the outputs mean. In order to keep the implementation simple and focus on understanding how the algorithms work and the model's explainability, the employee attrition dataset was chosen. Most of the time, interpretability is only considered and used in severe contexts such as healthcare, data security, weather prediction, safety, corruption prevention, etc. However, it may also be helpful in less severe contexts, like figuring out employee attrition, in my opinion. At the end of our study, we show how the models work on this data set and how to Explain what causes people to leave a group.

1.4: Question for Research

In this thesis, we have three core research questions which are given below:

RQ1. Which parts are most to blame for this problem?

RQ2. Does it helpful for any organization or company to take their future steps?

1.5: Research Objective

We want to do the following three things to answer the research questions.

RO1: Machine learning methods that can be explained will be used to test the input features. Then Humans will understand when and why the machine has predicted such a decision for which aspect of.

RO2: This paper also predicts the rate at which employees quit. By knowing this prediction, organizers can see where they are falling short and take steps to fix it. It must be beneficial to organizers who want to keep more employees.

1.6: The area of study

Imagine being a software engineer. You work with machines that can learn. One of your clients shows up with a dilemma. The problem is that he owns a factory where clothes are made. After just a few months of hiring people, they start leaving, making his factory lose a lot of money yearly. So, the client wants to know the problem and how to solve it. He might get a little nervous when you take employee information from the company's database and use machine learning algorithms to make predictions. Then some questions will arise in his mind:

1.First, can you explain why it was predicted that people quit their job?

2.What are the reasons for this forecast?

3.Which one has the most significant impact?

4.How can it be prevented?

To answer these questions, you'll need to use Explainable AI. When you used SHAP, you will explain the feature importance. After exploring the importance of feature, you can determine which features are mostly affected this issue. Knowing everything will enable a business's owner to quickly grasp the source of any issues, and hopefully lead to action to both prevent and address them.

1.7: How the chapter is put together

The rest of the thesis is put together like this. In Chapter 2, we look at research-related books and articles. Explainable machine learning and its algorithms will be covered in more detail in Chapter 2. We talked discussed how we did our research and analyzed it in Chapter 3 and 4. Regarding employee turnover, the following ideas have been put forward: In Chapter 5, we talked about this. Chapter 6 looks at how the research study we want to do turned out and what we learned from it. Chapter 6 is based on the end of our research study.

Chapter 2: Review of the Literature

This section discusses the previous research related to our research. Based on the results of the previous research, we have tried to reflect the following ideas (Szoplik & Ciuksza, 2021). Employee attrition is a long-standing issue that people have long sought to understand. As a result, various researchers have shared their knowledge with us. Cause of employee attrition or to predict this, different researchers have used different methodologies. Many have also applied multiple algorithms of machine learning. If we look at a recent research paper titled "Understanding employee attrition using explainable AI," we can see that Explainable is the most recent updated form of machine learning used in the study. Machine learning is explained in much details (“Intelligent Computing,” 2019).

The main objective of this research was to provide a thorough understanding of the explainable algorithm and its operation (Moeti et al., 2022). Using a dataset related to employee attrition, algorithms are explained. On this dataset, they based their algorithms. The accuracy, precision, recall, and F1 score values of the employee dataset are calculated in this study using a few algorithms. XGBoost, LightGBM, Random Forest, Naive Bayes, Logistic Regression, and SVM are among the algorithms. In this study, SHAP was used to explain the functions of the Force plot, Decision plot, and Summary plot. Many factors influencing employee attrition are clarified by their research. The factor's exact contribution to the problem as well as its source are unclear. These studies fall short of demonstrating any discernible relationship between the factors and their causes.

And this is the primary area of our study. We will use Explainable AI to determine how each dataset feature contributes to employee attrition. Is knowing even possible? Our main objective was to go into great detail about whether or not it was possible. Attempting to deduce the true value from the previously discussed predicted value is another option. For this, a "HR employee" dataset that was obtained from Kaggle was used. In this study, explainable machine learning algorithms were used to essentially confirm the causes of employee attrition.

With the help of an Explainable Machine Learning algorithm, we basically confirmed the underlying causes of employee attrition in this study and demonstrated the significance of each feature for this prediction. We employed SHAP for that. We were able to establish the significance of the factors using the "feature_importances_" function of the SHAP model. The Overtime feature, which has the highest importance, can be seen in the result, in table no. 3. Age comes next, then monthly income, etc. Additionally, using the Logistics Regression, Gaussian Naive Bayes, and SVM algorithms, we discovered accuracy, precision, and recall values that provide a more accurate idea than the findings of earlier research.

Chapter 3: Concept of XAI

3.1: Explainable artificial intelligence (XAI)

A collection of techniques and procedures known as explainable artificial intelligence (XAI) aims to improve human comprehension and confidence in the findings and outputs produced by machine learning algorithms. When discussing an AI model, its anticipated outcomes, and any potential biases, the term "explainable AI" is used. It aids in describing the decision-making algorithm's fairness, accuracy and results.

Your machine learning models' predictions can be understood and made sense of using a set of tools and frameworks called explainable AI. For a business to develop trust and confidence in AI models before putting them into production, explainable AI is crucial. A business that develops AI responsibly can benefit from AI that is simple to understand.

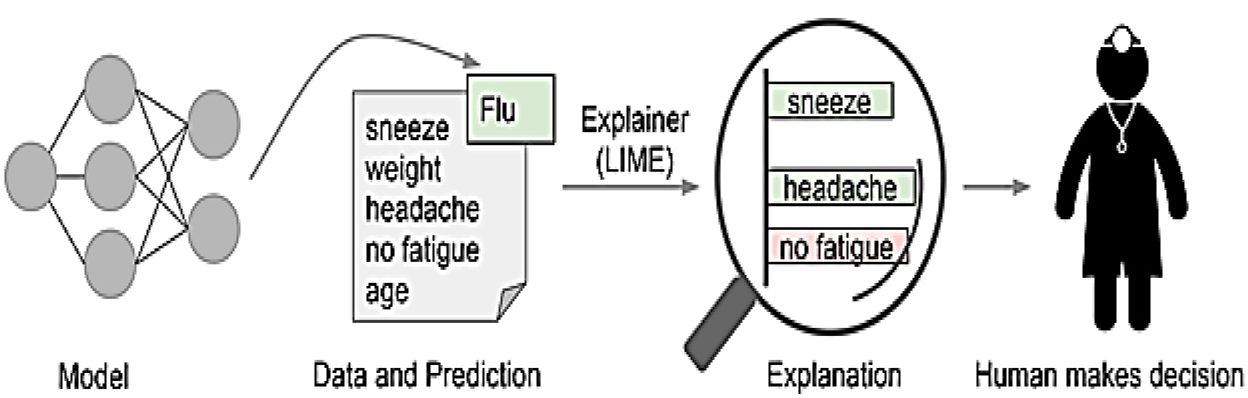


Figure-1: Explainable AI

You need to understand what XAI is and why it's important first. Black boxes, which take input and produce output but are impossible to understand how they operate, are how AI algorithms frequently operate. Humans should be able to understand an algorithm's reasoning behind its output thanks to XAI.

For instance, deep learning is a technique that many AI algorithms employ to identify patterns from vast amounts of training data. A neural network method called "deep learning" imitates the wiring of the human brain. The process by which a deep learning algorithm arrived at a prediction or decision can be difficult or impossible to understand, just like how a person thinks.

Decisions regarding hiring and use cases involving financial services, such as credit ratings and loan approvals, are crucial and merit explanation. However, if one of those algorithms makes a poor recommendation, No one is likely to suffer any physical harm (at least not immediately). However, there are numerous instances where the outcomes are significantly worse.

3.2: How does explainable AI work?

These principles help describe the kinds of outcomes you can anticipate from XAI, but they also need to describe how to achieve those outcomes. It might be useful to divide XAI into the following three categories:

• **Data with context.** What data did a model get trained on? Why was that information chosen? How did they determine whether it was just? Was bias eradicated in any way?

• **Logic-based predictions.** To achieve a particular result, which model components were activated or used.

• **Easily understandable codes.** What components make up the model, and how do they interact to produce the result or prediction?

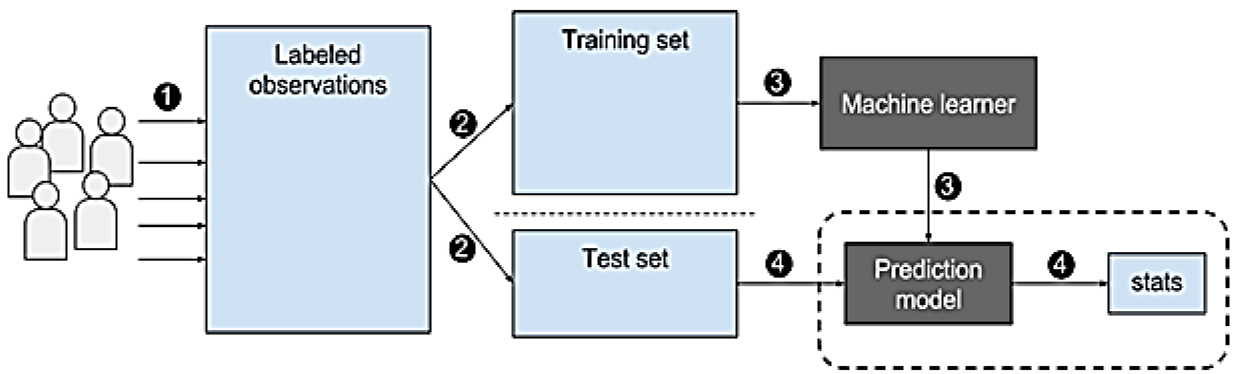


Figure-2: Working Process of Explainable AI

Explainable data is the only type of data that is, at least in theory, easy to get, and this is especially true for neural networks. Much research is still going on to figure out how to make predictions and algorithms that can be explained. There are two ways to look at explainability right now:

•**Modeling using proxies.** To get as close to the accurate model as possible, a different kind of model, such as a decision tree, is used. Since it is only an estimate, it might differ from the actual model results.

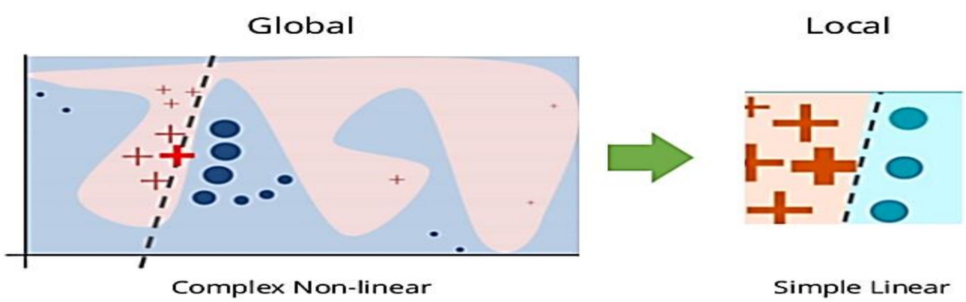
•**Make things easy to understand**. Models are created to be simple to describe. This approach might result in a model that is less reliable or accurate at making predictions.

Sometimes referred to as "white box" models, simple models are simple to understand. Explainable white box AI makes business settings more common by enabling users to understand why it chooses the actions that it does. These models can't compete with black box algorithms in terms of technical accomplishment. Decision trees, Bayesian networks, sparse linear models, and other techniques are examples of those that can be explained.

3.3 Local Interpretability and Global Interpretability

Interpretability measures how accurately a person can predict the outcome of the model. A machine-learning model is more interpretable if it is clear why certain choices or predictions were made. If a model's decisions are simpler for a person to understand than those of another model, then it is easier to understand it than the other model. The terms "explainable" and "interpretable" will be used interchangeably.

There are two types of interpretability: local and global.



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In order to explain how a model generates each of its predictions, it must be local interpretable. People are more likely to use the model's recommendations and other factors when they can more readily trust it. The ability to interpret a model globally refers to its ability to do so.

When describing how something can be interpreted locally, for example, LIME is used, whereas SHAP is used to describe how it can be interpreted globally.

3.4: Local Interpretable Model Explanation (LIME)

In their paper Local interpretable model-agnostic explanations (LIME), the authors offer a detailed method for utilizing local surrogate models. Instead of training a global surrogate model, LIME concentrates on training local surrogate models to explain specific predictions ("Intelligent Data Engineering and Automated Learning – IDEAL 2019," 2019). Surrogate models are developed to make predictions that are similar to what the black box model on which they are based would say.

This concept is obvious. First, disregard the training data and consider a model that is a black box into which you can insert data points to obtain model predictions. If you want, you can always peek inside the box. You are attempting to comprehend why a particular prediction was made by the machine learning model. LIME examines the results of feeding the machine learning model various iterations of your data and seeing what happens to the predictions. A new set of data is created by LIME that includes the black box model's predictions as well as modified samples. On this fresh dataset, LIME then develops a computable model. The weights of the model are determined by the proximity of the sampled instances to the relevant instance (Fiosina, 2022). Because approximations are used, LIME is much faster to compute than SHAP in terms of time.

3.5 SHAP (SHapley Additive exPlanations)

SHAP, which stands for "SHapley Additive Explanations," is a way to explain how each prediction works. SHAP is based on the best possible Shapley values for the game (Alani & Awad, 2022). SHAP's goal is to figure out how each feature of an instance affects the prediction of that instance. Coalitional game theory is used by the SHAP explanation method to figure out Shapley values. The feature values of a data instance work together like members of a group (Zaidan et al., 2022).

SHAP runs quickly on models like gradient boosted and random forest, but it takes too long to run on models like k-nearest neighbor. By summarizing the data, you can cut the run time down by a lot, but you lose consistency and accuracy.

Game theory is a strong theoretical base for SHAP. The prediction is about the same for each of the feature values. We get different explanations for the difference between the prediction and the average prediction. SHAP links the values of LIME and Shapley. This is a great way to learn more about both ways. It also helps to bring the field of machine learning that can be understood together (Molnar, 2022).

Chapter-4: Methodology and Data Description

4.1 Workflow

To Understanding the workflow of machine learning, we can separate the machine learning workflow in 3 stages:

1. Data collection
2.Pre-processing of data
3.Looking into the model that will work best with the given data
4.Training and testing
5.Evaluation
6.Prediction Result (Pant, 2019)

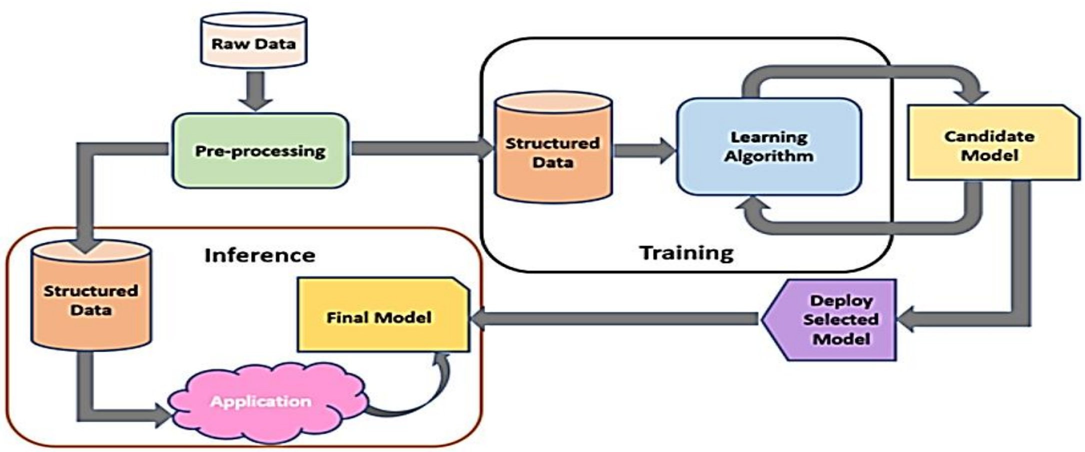

Figure-4: Basic ML Workflow

As well as discussing these topics and their effects on the performance of machine learning models, we will also discuss data pre-processing, data cleaning, feature exploration, and feature engineering (Pant, 2019). A few pre-modelling steps that can enhance the performance of the model are also covered.

4.2 Dataset Description:

In this section, we go over the specifics of the dataset that was thought to be implemented. The HR Employee Attrition Dataset, a made-up open source dataset with 1470 data instances, was developed by data scientists at HR. The dataset contains data on attrition and employee performance. To determine whether an employee will leave the company (churn) or not, 35 predictor (dependent)variables are considered. Six of the remaining 35 predictors are numerical variables, leaving 29 categorical variables.

4.2.1 Dataset:

We can identify, the dataset is mark of 1470 entries, 9 categorical features, and 25 numerical features when we import the libraries which essential for this use-case. We used "Employee Number," as an index for Pandas data frame which is specific to each employee. Here is the dataset feature analyses and related information given:

Table-1: Exploratory analysis to find out the missing data points if any

Column	Non -Null Count	Data Type	Column	Non-Null Count	Data Type
Age	1470	int64	MonthlyRate	1470	int64
Attrition	1470	object	NumCompaniesWorked	1470	int64
BusinessTravel	1470	object	Over18	1470	object
DailyRate	1470	int64	OverTime	1470	object
Department	1470	object	PercentSalaryHike	1470	int64

DistanceFromHome	1470	int64	PerformanceRating	1470	int64
Education	1470	int64	RelationshipSatisfaction	1470	int64
EducationField	1470	object	StandardHours	1470	int64
EmployeeCount	1470	int64	StockOptionLevel	1470	int64
EnvironmentSatisfaction	1470	int64	TotalWorkingYears	1470	int64
Gender	1470	object	TrainingTimesLastYear	1470	int64
HourlyRate	1470	int64	WorkLifeBalance	1470	int64
JobInvolvement	1470	int64	YearsAtCompany	1470	int64
JobLevel	1470	int64	YearsInCurrentRole	1470	int64
JobRole	1470	object	YearsSinceLastPromotion	1470	int64
JobSatisfaction	1470	int64	YearsWithCurrManager	1470	int64
MaritalStatus	1470	object			
MonthlyIncome	1470	int64			

The entire dataset is complete and contains no missing data.

4.2.2 Data Exploration:

There are several descriptive statistics for numerical variables, including "count", "mean', "std", "min", 25%, 50%, and 75% values and "max".

The shortforms' variable indicates:

Count - Overall number of occurrences

Mean- mean value for the variable

Std (Standard Deviation)- spread for the variable's range of values

Min- Minimum value of that variable in the given set of instances

Max-Maximum value of that variable in the given set of instances

Table-2: The different types of predictor variables

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0
mean	36.923810	802.485714	9.192517	2.912925	1.0
std	9.135373	403.509100	8.106864	1.024165	0.0
min	18.000000	102.000000	1.000000	1.000000	1.0
25%	30.000000	465.000000	2.000000	2.000000	1.0
50%	36.000000	802.000000	7.000000	3.000000	1.0
75%	43.000000	1157.000000	14.000000	4.000000	1.0
max	60.000000	1499.000000	29.000000	5.000000	1.0

EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel	JobSatisfacti
1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	1470.00000
1024.865306	2.721769	65.891156	2.729932	2.063946	2.728571
602.024335	1.093082	20.329428	0.711561	1.106940	1.102846
1.000000	1.000000	30.000000	1.000000	1.000000	1.000000
491.250000	2.000000	48.000000	2.000000	1.000000	2.000000
1020.500000	3.000000	66.000000	3.000000	2.000000	3.000000
1555.750000	4.000000	83.750000	3.000000	3.000000	4.000000
2068.000000	4.000000	100.000000	4.000000	5.000000	4.000000

RelationshipSatisfaction	StandardHours	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear
1470.000000	1470.0	1470.000000	1470.000000	1470.000000
2.712245	80.0	0.793878	11.279592	2.799320
1.081209	0.0	0.852077	7.780782	1.289271
1.000000	80.0	0.000000	0.000000	0.000000
2.000000	80.0	0.000000	6.000000	2.000000
3.000000	80.0	1.000000	10.000000	3.000000
4.000000	80.0	1.000000	15.000000	3.000000
4.000000	80.0	3.000000	40.000000	6.000000

WorkLifeBalance	YearsAtCompany	YearsInCurrentRole	YearsSinceLastPromotion	YearsWithCurrManager
1470.000000	1470.000000	1470.000000	1470.000000	1470.000000
2.761224	7.008163	4.229252	2.187755	4.123129
0.706476	6.126525	3.623137	3.222430	3.568136
1.000000	0.000000	0.000000	0.000000	0.000000
2.000000	3.000000	2.000000	0.000000	2.000000
3.000000	5.000000	3.000000	1.000000	3.000000
3.000000	9.000000	7.000000	3.000000	7.000000
4.000000	40.000000	18.000000	15.000000	17.000000

Categorical variables have a list of their value types. The list of distinct types of values (or classifications) that a particular parameter can take in a given set of observations is indicated by these value types. Some categorical variables, like "Gender", "Overtime" and other terms, have binary classification values, such as "Male", "Female" and "Yes", "No" for "Gender" and "Yes"

"No" for "Overtime" while others, like "Education Field", "Job Role", "Department", "Business Travel" and "Marital Status" have multiple classification values.

4.3 Explaining predictions with SHAP

This section would be interesting, here we tried to explore why the model predict that why employee has a strong probability to quit or not. The easiest way to figure out which parameters have a big impact on predictions is to look at the "feature_ importances_" attribute on a trained model.

The idea behind the importance of SHAP features is simple: Important things are those with high absolute Shapley values. Since we want to know the global importance, we take the average of the absolute Shapley values for each feature (Molnar, 2022). The feature importance plot is useful, but it doesn't show anything else besides how important each feature is.

	Importance float64 3.18441058550199 - 7.789284587...
OverTime	7.789284587575185
Age	5.782942889535979
MonthlyIncome	5.079685339622612
JobSatisfaction	5.063329736063949
StockOptionLevel	4.766576966787455
DistanceFromHome	4.732115044474903
EnvironmentSatisfaction	4.67374379726716
RelationshipSatisfaction	4.367532022379959
JobLevel	3.844877395186079
MonthlyRate	3.7945240239121105
DailyRate	3.5659643638499365
JobInvolvement	3.3665935845479162
NumCompaniesWorked	3.3055932601911757
YearsWithCurrManager	3.203628103551129
HourlyRate	3.18441058550199

Figure-4: Feature importance

“Overtime” at most significant importance feature to this occurrence, after that “Age” comes. Than “MonthlyIncome”, than “JobSatisfaction”, and one by one comes after.

However, this does not indicate any immutable potential. This may vary depending on the variation in dataset and sample characteristics.

4 .4 Model Building

I this section, we trained and testing our data with Logistic Regression, Gaussian Naive Bayes, Support Vector Machine (SVM) models. We tried to out Accuracy, Precision, Recall values accurately.

Check out how the metrics are calculated:

Accuracy: Accuracy is a metric that shows how well the model works in all classes as a whole. It works well when all classes have the same weight. It is worked out by dividing the number of right guesses by the total number of guesses.

$$\boldsymbol{Accuracy = \frac{Truepositive + Truenegative}{Truepositive + Truenegative + Falsepositive + Falsenegative}}$$

Precision: Precision is calculated as the number of correctly identified positive samples divided by the total number of samples that were identified as positive. Precision is a measure of how well the model can tell if a sample is positive or not.

$$\boldsymbol{Precision = \frac{Truepositive}{Truepositive + Falsepositive}}$$

The goal of precision is to label all positive samples as positive and not mistakenly label a negative sample as positive.

Recall: The ratio of the number of Positive samples that were correctly labeled as Positive to the total number of Positive samples is used to figure out the recall. The model's ability to find positive samples is measured by its recall. The more positive samples that are found, the higher the recall. Only how the positive samples are put into groups is important to the recall. This is true no matter how the negative samples are put into groups, such as for precision.

$$\boldsymbol{Recall = \frac{Truepositive}{Truepositive + Falsenegative}}$$

Chapter-5: Results and Discussions

This section looks at the findings and assessments from the research study we've suggested.

5.1 Metric Reporting

Table-3: Accuracy metrics for various models

Model Name	Accuracy	Precision	Recall
Logistic Regression	87.14	90	97.3
Naïve Bayes	83.19	88.14	80
SVM	95.8	92.42	98.48

Table -3 is a graph that shows how the recall, precision, and accuracy of each model compare. The graph shows that, compared to the other metrics, the recall rate for all the models has been high in general. Except for one model (Naive Bayes), recall values always fell between the 90th and 95th percentiles. As the graph shows, Logistic Regression, Naive Bayes, and SVM all have about the same accuracy rates (87.14 percent, 83.19 percent, and 95.8 percent, respectively), and there isn't much difference between them in the real world. As the graph shows, Support Vector Machine is the most accurate model, with a score of 92.42%. The other models have scores between 83% and 95%.

Chapter-6: Conclusion and Future work

In this study, SVM, LR, and Nave Bayes, three cutting-edge machine learning techniques, were used to predict employee attrition in comparison. The accuracy scores obtained by the used machine learning techniques were 95.8% for the SVM technique, 87.14% for the LR technique, and 83.19% for the Naive Bayes technique. Utilizing the SHAP library, it is made clear the significance of employee attrition causes. The results of our study assist businesses in reducing staff turnover. We will use deep learning techniques to predict employee attrition in the future, given the limitations of the current study. We will also use deep learning techniques to expand the dataset's feature space in order to produce more accurate results.

Future Work:

The employee attrition prediction by using the three advanced machine learning techniques SVM, LR, and Naive Bayes, were applied in comparison in this study. The applied machine learning techniques achieved accuracy scores of 87.14% by LR technique, 83.19% by Naïve Bayes technique, and 95.8% by SVM technique.Our research findings help organizations overcome employee attrition. The study limitations and in future direction, we will apply the deep learning techniques to predict the employee attrition. Moreover, we will enhance the dataset feature space to obtain more accurate results by using dee learning techniques (Raza et al., 2022).

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