ESE-1 SUBMISSION REPORT

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Class: 4MDS

Subject name: Neural Networks and Deep Learning

Subject code: MDS471

Project name: AttriNet– Predictive HR Attrition Intelligence

Submitted to:

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Table of Contents:

Topic: Model Presentation on HR Analytics Dataset
Dataset: IBM HR Analytics Employee Attrition Dataset
Source: IBM HR Analytics Employee Attrition & Performance

1. Dataset Selection:

This dataset contains employee information for 1,470 individuals from IBM. The aim is to analyze factors contributing to employee attrition (whether an employee leaves or stays) and to eventually build a prediction model.

1.1 Column Descriptions:

Column Name	Description
Age	Age of the employee
Attrition	Whether the employee left the company (Yes/No)
Business Travel	Frequency of travel (Rarely, Frequently, Non-Travel)
Daily Rate	Daily salary rate of the employee
Department	Department where the employee works (Sales, R&D, HR)
Distance From Home	Distance from home to office (in kilometres)
Education	Education level (1=Below College to 5=Doctor)
Education Field	Field of study (Life Sciences, Technical Degree, etc.)
Employee Number	Unique ID for each employee
Environment Satisfaction	Satisfaction with work environment (1 to 4)
Gender	Male or Female
Hourly Rate	Hourly wage rate

Job Involvement	Level of involvement in the job (1 to 4)
Job Level	Job seniority level
Job Role	Role (e.g., Sales Executive, Manager, etc.)
Job Satisfaction	Job satisfaction score (1 to 4)
Marital Status	Marital status (Single, Married, Divorced)
Monthly Income	Monthly salary
Num Companies Worked	Number of companies previously worked at
Over Time	Whether the employee works overtime
Percent Salary Hike	Percentage hike in salary
Performance Rating	Performance rating (1 to 4)
Relationship Satisfaction	Satisfaction with relationships at work (1 to 4)
Stock Option Level	Level of stock option benefits
Total Working Years	Total years of experience
Training Times Last Year	Number of training sessions attended in the last year
Work Life Balance	Rating of work-life balance (1 to 4)
Years At Company	Total years at the current company
Years In Current Role	Years in current job role
Years Since Last Promotion	Years since last promotion
Years With Curr Manager	Years with current manager

All columns are either numerical, ordinal, or categorical. The target variable is **Attrition**.

2. Justification of Relevance for choosing the dataset:

Employee attrition causes loss of talent, training costs, and disruption in team dynamics. Predicting which employees are likely to leave helps HR departments take preventive action. The dataset contains relevant HR metrics (satisfaction, salary, overtime, etc.) that impact attrition, making it a great choice for both EDA and deep learning classification.

This also matches real-world problems faced in companies, making it highly relevant for building neural networks (like ANN/DNN), which can capture nonlinear relationships in such data.

3. Exploratory Data Analysis:

Dataset shape: (1470,35)

Missing values: No missing values

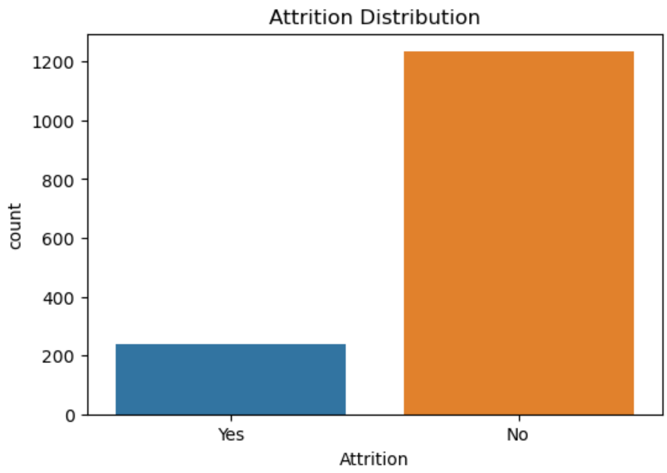
Unique values per column:

Column Name	Count
Age	43
Attrition	2
BusinessTravel	3
DailyRate	886
Department	3
DistanceFromHome	29
Education	5
EducationField	6
EmployeeCount	1
EmployeeNumber	1470
EnvironmentSatisfaction	4
Gender	2
HourlyRate	71

JobInvolvement	4
JobLevel	5
JobRole	9
JobSatisfaction	4
MaritalStatus	3
MonthlyIncome	1349
MonthlyRate	1427
NumCompaniesWorked	10
Over18	1
OverTime	2
PercentSalaryHike	15
PerformanceRating	2
RelationshipSatisfaction	4
StandardHours	1
StockOptionLevel	4
TotalWorkingYears	40
TrainingTimesLastYear	7
WorkLifeBalance	4
YearsAtCompany	37
YearsInCurrentRole	19
YearsSinceLastPromotion	16
YearsWithCurrManager	18

3.1 Visuals with appropriate labels and interpretations:

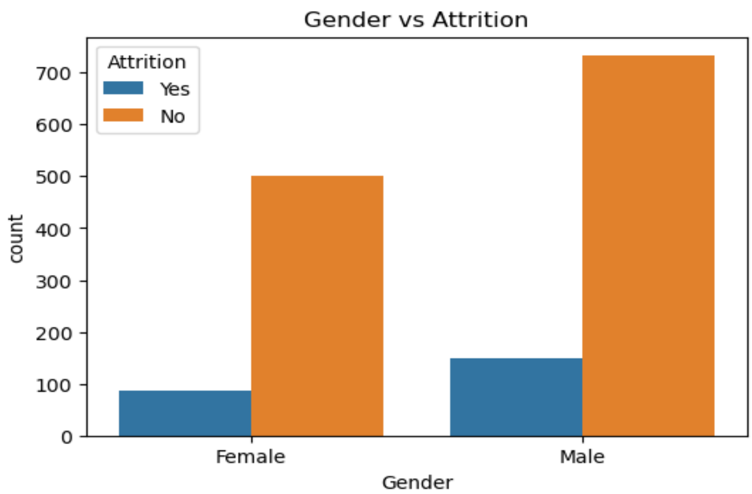
(i) <u>Count plot for Attrition Distribution:</u>



Interpretation:

The count plot of "Attrition Distribution" shows how many employees left the company compared to how many stayed. The bar for employees who did not leave ("No") is much taller, meaning most people stayed with the company. Only a smaller group left ("Yes"), showing that it was more common for employees to remain at their jobs during the period this data covers.

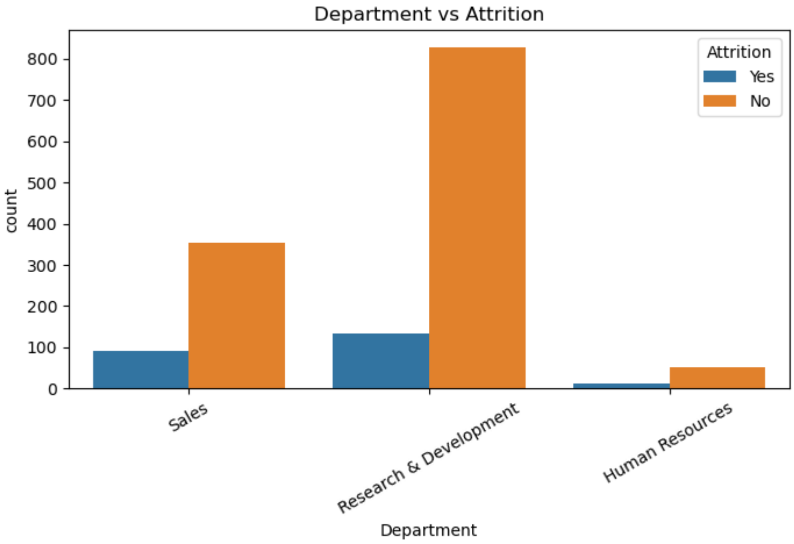
(ii) Count plot for Gender:



Interpretation:

The count plot for "Gender vs Attrition" shows how many male and female employees left the company compared to how many stayed. For both genders, the bar representing employees who did not leave ("No") is much higher than the bar for those who left ("Yes"). While the overall counts of males and females differ, in both groups, it is clear that staying with the company is much more common than leaving. This suggests that, regardless of gender, most employees remained at their jobs, and only a smaller portion experienced attrition. The plot helps quickly compare attrition patterns between males and females, showing retention was strong for both groups in this dataset.

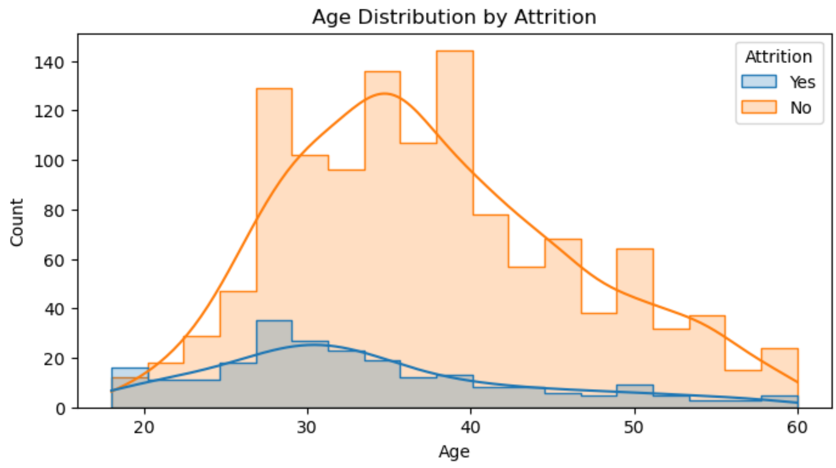
(iii) Count plot for Department:



Interpretation:

The count plot for "Department vs Attrition" shows how employee attrition varies across the company's different departments. In this visualization, each department—Sales, Research & Development, and Human Resources—has two bars: one for employees who stayed ("No") and one for those who left ("Yes"). It is clear that in all departments, most employees did not leave the company, as the "No" bars are much taller than the "Yes" bars. The Research & Development department has the highest number of employees overall, with the majority staying. Sales also shows more employees staying than leaving, but with higher attrition counts compared to the other departments. Human Resources has the fewest employees and also shows attrition, though to a lesser degree.

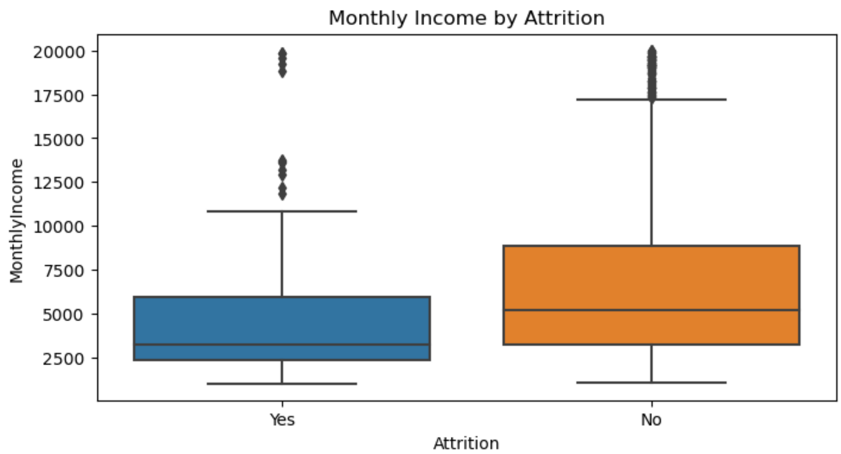
(iv) Distribution for Age:



Interpretation:

The plot for "Age Distribution by Attrition" shows how employee age relates to whether they stayed with the company or left. Each age group is represented on the x-axis, with the y-axis showing the number of employees. The plot uses different colors for employees who left ("Yes") and those who stayed ("No"). Employees who stayed are most common in the age range of about 30 to 40 years, as shown by the tall, broad orange area. The group that left the company (blue) also peaks in the late 20s to early 30s but is much smaller compared to those who stayed. In both categories, there are fewer very young and older employees, but most employees—especially those who stayed—are clustered around ages 30 to 40.

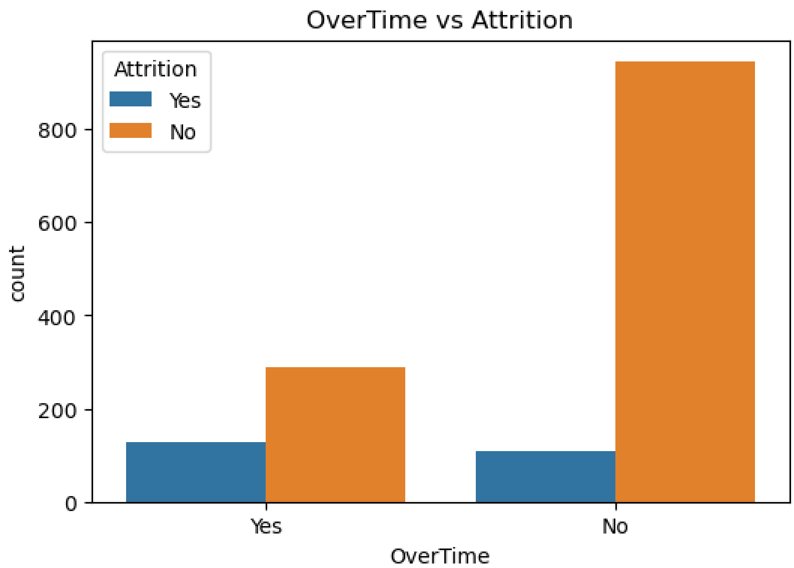
(v) Boxplot for Monthly Income by Attrition:



Interpretation:

The boxplot for "Monthly Income by Attrition" compares the distribution of employee monthly incomes between those who stayed with the company ("No" attrition) and those who left ("Yes" attrition). The plot shows that employees who stayed generally have higher median monthly incomes, and their income range is wider compared to those who left. The boxes represent the middle 50% of incomes for each group, with the median line inside each box. For the "Yes" group, the median and upper income values are noticeably lower, and there are several outliers at the higher end. In contrast, the "No" group's income expands to higher values, both in the interquartile range and in the outliers. This implies that employees with higher and more varied incomes are more likely to stay with the company, while those with lower incomes are more likely to leave.

(vi) **Count plot for Overtime:**

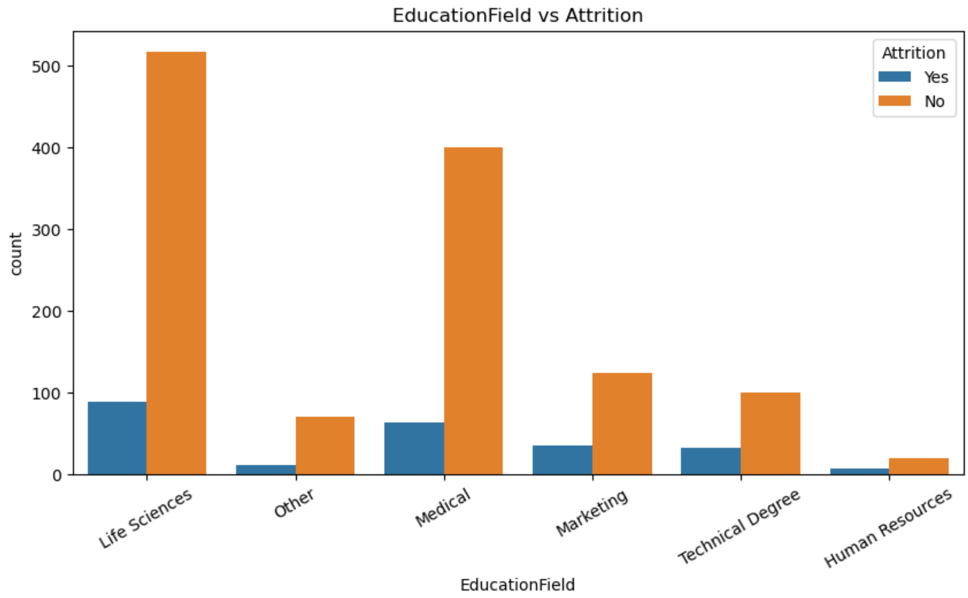


Interpretation:

The countplot for "OverTime vs Attrition" shows how working overtime relates to whether employees stay with the company or leave. The x-axis has two categories: "Yes" for employees who worked overtime and "No" for those who did not. Each category is split into two bars showing the number of employees who left ("Yes" attrition) and those who stayed ("No" attrition).

From the plot, it is clear that employees who do not work overtime are much more likely to stay with the company, as shown by the tall orange "No" bar. In the group that did work overtime, a higher number of employees left compared to those who did not, since the blue "Yes" bar is noticeably higher for overtime workers than for non-overtime workers.

(vii) Education Field Count plot:

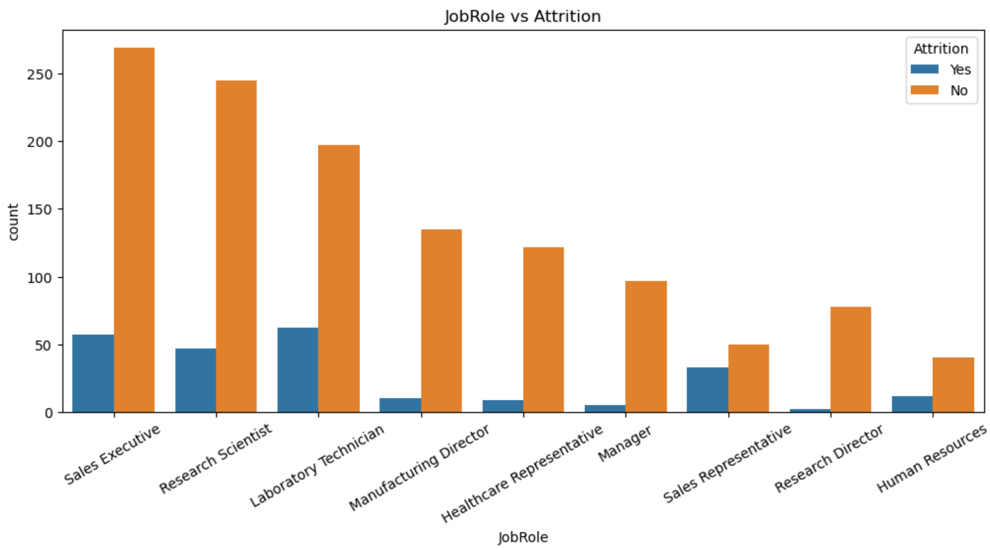


Interpretation:

The countplot for "EducationField vs Attrition" displays the number of employees from each educational background who left the company compared to those who stayed. Each education field—such as Life Sciences, Medical, Marketing, Technical Degree, Other, and Human Resources—has two bars: one for employees who stayed ("No") and one for those who left ("Yes"). The plot shows that, for every field, the majority of employees did not leave, as seen by the higher "No" bars.

Life Sciences and Medical have the highest employee counts, and most people in these fields chose to stay with the company. In every category, the number of employees who left is noticeably smaller than those who stayed. This indicates that, regardless of educational background, most employees remained at their jobs. However, a small number of departures is visible across all education fields, highlighting that attrition occurs in every group but is far less common than retention. This visualization makes it clear that retention is consistently high for all education fields in the dataset.

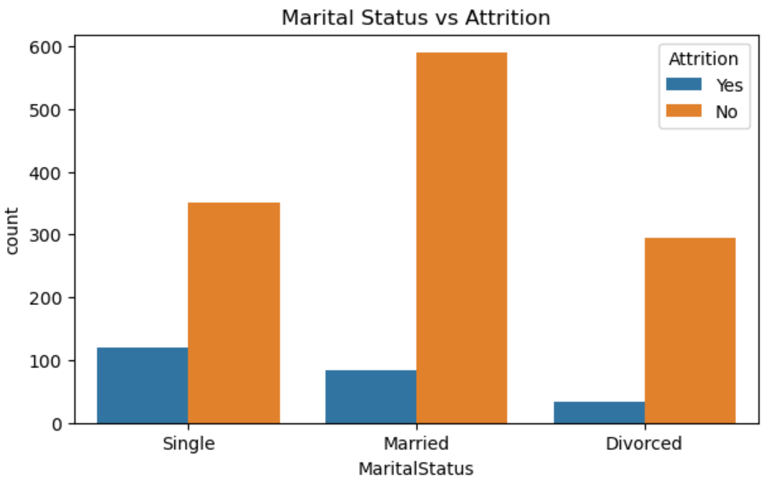
(viii) Job Role Count plot:



Interpretation:

The countplot for "JobRole vs Attrition" shows how employee turnover is distributed across different job roles. Each job role on the x-axis has two bars indicating the number of employees who stayed ("No") and those who left ("Yes"). The visualization reveals that for all job roles, most employees stayed with the company, as represented by the much taller "No" bars. Some roles, like Sales Executive, Research Scientist, and Laboratory Technician, have a relatively higher count of both staying and departing employees due to their larger workforce. Other roles, such as Research Director and Manager, show very low attrition with only a small number of employees leaving. This plot highlights that while attrition is present in every job role, it is generally much less frequent than retention, and certain roles experience higher employee turnover simply because they have a larger staff.

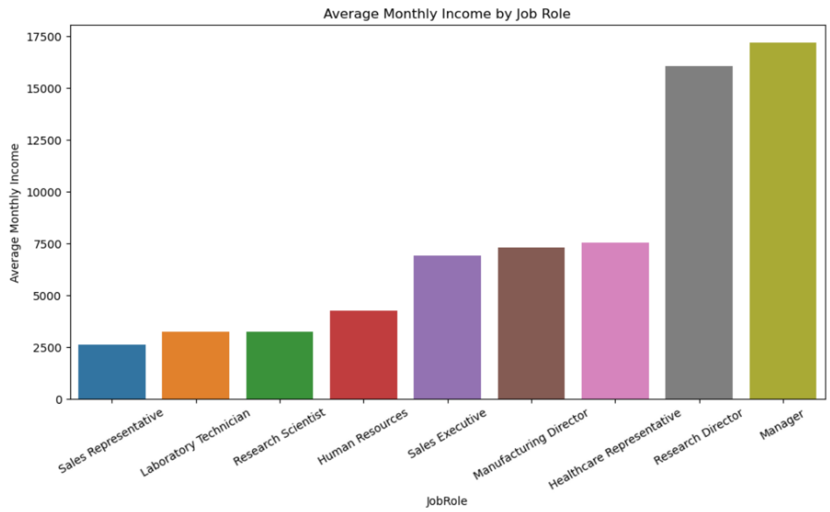
(ix) Marital Status Count plot:



Interpretation:

The countplot for "Marital Status vs Attrition" compares how employee turnover differs among single, married, and divorced employees. In the plot, each marital status category has two bars—one for employees who stayed ("No") and one for those who left ("Yes"). The graph shows that across all marital statuses, most employees did not leave the company, as indicated by the much taller "No" bars. Married employees make up the largest group by far, with the highest number staying at the company, while singles and divorced employees also show higher retention than attrition. However, among the smaller proportions who left, single employees appear to have a slightly higher attrition count compared to married and divorced groups. Overall, the visualization makes it clear that employee retention is high in every marital status group, but singles experience relatively more attrition than others.

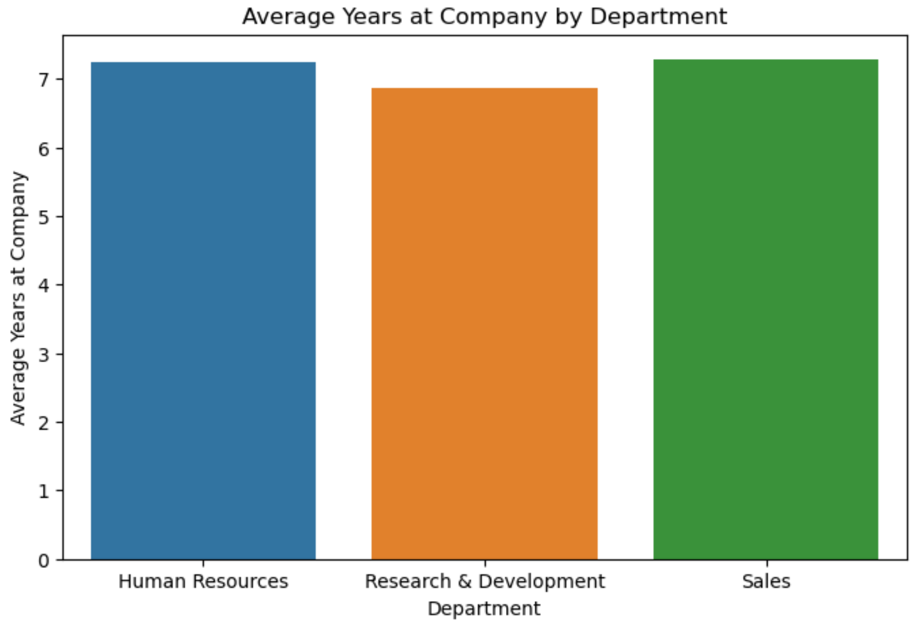
(x) Barplot for Average Monthly Income by Job Role:



Interpretation:

The barplot for "Average Monthly Income by Job Role" shows a clear comparison of how monthly earnings differ according to each position within the company. From the plot, it's evident that roles like Research Director and Manager have the highest average monthly incomes, standing out significantly above the rest. In the middle range, positions such as Healthcare Representative, Manufacturing Director, and Sales Executive earn considerably more than roles like Human Resources, Research Scientist, Laboratory Technician, and Sales Representative, which are clustered towards the lower end of the income scale. This visual makes it clear that managerial and directorial positions are rewarded with much higher salaries, while technical and entry-level job roles tend to receive lower average monthly incomes. The ordering in the plot allows for quick identification of the most and least lucrative roles in the organization.

(xi) Barplot for Average Years at Company by Department:



Interpretation:

The barplot for "Average Years at Company by Department" compares how long, on average, employees from each department have stayed with the company. The chart shows that the Human Resources and Sales departments have the highest average tenure, with employees in these groups remaining with the company for just over seven years on average. The Research & Development department follows closely, with an average just below seven years. This visual highlights that employees tend to have similar lengths of service across all departments, with only slight differences between them, suggesting a consistent pattern of employee retention regardless of department.

4. Proposed neural network/deep learning architecture

4.1 Data Preprocessing:

Before the data can be fed into the neural network, it must be preprocessed. This involves two key steps:

1. **Categorical Feature Encoding:** The non-numeric columns in the dataset (like Gender, Department, OverTime, etc.) must be converted into a numerical format. **One-hot encoding** is the recommended approach here, as it creates a new binary column for each category, preventing the model from assuming an incorrect ordinal relationship between categories.
2. **Numerical Feature Scaling:** The numerical features (like Age, MonthlyIncome, YearsAtCompany, etc.) should be scaled. **Standardization** (using StandardScaler) is recommended. This process transforms the data to have a mean of 0 and a standard deviation of 1, which helps the network's optimization algorithm (gradient descent) to converge more quickly and effectively.

4.2 Network Architecture:

The proposed neural network consists of an input layer, three hidden layers, and an output layer.

- **Input Layer:** The number of neurons in the input layer is equal to the number of features in our preprocessed dataset. For example, after one-hot encoding all categorical variables and including all numerical ones, if we have 49 features, the input layer will have **49 neurons**.
- **Hidden Layers:** The network has three densely connected hidden layers that learn complex patterns from the data.
    - **First Hidden Layer: 64 neurons** with a **ReLU (Rectified Linear Unit)** activation function. ReLU helps mitigate the vanishing gradient problem and introduces non-linearity.
    - **Dropout Layer:** A dropout layer with a rate of **0.3** (or 30%) is added after the first hidden layer. Dropout is a regularization technique that helps prevent overfitting by randomly setting a fraction of input units to 0 at each update during training.

- **Second Hidden Layer: 32 neurons**, also with a **ReLU** activation function.
- **Dropout Layer:** Another dropout layer with a rate of **0.3** is added after the second hidden layer.
- **Third Hidden Layer: 16 neurons**, also with a **ReLU** activation function.
- **Dropout Layer:** Dropout layer with a rate of 0.2 is added after the third hidden layer.

- **Output Layer:** The final layer is a dense layer with **1 neuron** and a **Sigmoid** activation function. The sigmoid function is ideal for binary classification as it squashes the output value into a range between 0 and 1, which can be interpreted as the probability of the employee leaving the company (attrition).

4.3 Compilation and Training:

To prepare the model for training, we need to configure the learning process.

- **Optimizer:** We use the **Adam optimizer**. Adam is an efficient and widely used optimization algorithm that adapts the learning rate during training.
- **Loss Function:** The loss function is **binary_crossentropy**. This is the standard loss function for binary classification problems, as it measures the difference between the predicted probabilities and the actual binary labels.
- **Metrics:** We monitor the **accuracy** of the model during training and evaluation to gauge its performance.

5. Justification for the chosen model

5.1 ANN Model:

The ANN, specifically a Multi-Layer Perceptron (MLP), serves as a powerful and robust baseline model for this classification task. Its suitability is based on the following reasons:

1. **Capturing Complex Non-Linearity:** The factors driving employee attrition are rarely simple or linear. An ANN's architecture, with its multiple layers and non-linear activation functions (like ReLU), is exceptionally good at modeling the complex, subtle, and interactive relationships between employee attributes like JobSatisfaction, MonthlyIncome, and YearsSinceLastPromotion.
2. **Handling High-Dimensional Feature Space:** After preprocessing our categorical variables using one-hot encoding, the number of input features expands significantly. ANNs are inherently well-suited to handle this high dimensionality, effectively

learning from a wide array of inputs without being overly impacted by the "curse of dimensionality" that can affect other models.

3. **Proven Performance and Flexibility:** ANNs are a well-established and proven architecture for a wide range of classification problems, including those with tabular data. They are highly flexible and can be scaled or adjusted (e.g., by adding more layers or neurons) to fit the complexity of the dataset, making them a reliable choice for achieving high predictive accuracy.

5.2 TabNet Model:

While the ANN is powerful, it often functions as a "black box," making it difficult to understand *why* it makes a certain prediction. For an HR use case, interpretability is crucial for taking action. This is why TabNet is an excellent and more advanced choice.

1. **Built-in Interpretability (The Key Advantage):** TabNet was specifically designed by Google Research to provide interpretability for tabular data, something traditional deep learning models lack.
    - It uses a **sequential attention mechanism** that mimics how a human might analyze data. At each step in its decision-making process, it intelligently selects the most relevant features to focus on.
    - This allows us to not only get a prediction but also to visualize **which features were most important** for that specific prediction. For HR, this is invaluable. Instead of just knowing an employee is at risk, TabNet can tell us that the risk is high *because* of factors like OverTime, JobRole, and StockOptionLevel. This provides clear, actionable insights for retention strategies.
2. **High Performance with Less Preprocessing:** TabNet often achieves state-of-the-art performance, competitive with or even exceeding traditional models like Gradient Boosting. Crucially, it does not strictly require one-hot encoding. It can process raw numerical features and learn its own internal representations (embeddings) for categorical variables, which can lead to more efficient learning and better performance by avoiding sparse feature sets.
3. **End-to-End Learning:** TabNet is a single, integrated deep learning model. Its feature selection and learning processes are combined, allowing it to learn rich, hierarchical representations of the data without the need for extensive manual feature engineering.

6. Flowchart:

The flow chart is given below:

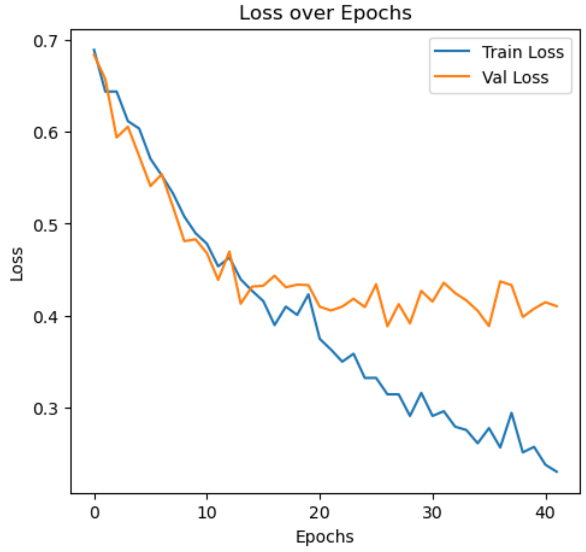
7. Results (Output screenshots):

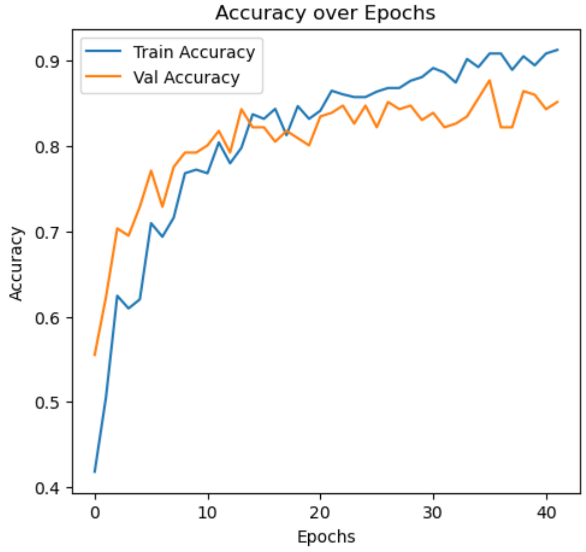
7.1 ANN Model:

7.1.1 Model summary:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 64)                3584

 dropout (Dropout)           (None, 64)                0

 dense_1 (Dense)             (None, 32)                2080

 dropout_1 (Dropout)         (None, 32)                0

 dense_2 (Dense)             (None, 16)                528

 dropout_2 (Dropout)         (None, 16)                0

 dense_3 (Dense)             (None, 1)                 17

=================================================================
Total params: 6209 (24.25 KB)
Trainable params: 6209 (24.25 KB)
Non-trainable params: 0 (0.00 Byte)
```

7.1.2 Loss curve and Accuracy curve:





<u>Interpretation:</u>

The loss curves show a consistent downward trend in both training and validation loss, which means the model is learning well and not stuck in a

plateau. While the validation loss flattens slightly after epoch 15 and shows small fluctuations, it does not diverge drastically from the training loss — indicating minimal overfitting. The training loss continues to improve, which suggests the network is still extracting patterns from the data.
The accuracy curves follow a healthy upward trend, with validation accuracy stabilizing around 80–84% and training accuracy reaching close to 90%. The gap between the two curves remains small, which is a sign of good generalization. This balance, combined with your AUC score of 0.78, shows that your ANN is performing well without serious overfitting, making these plots strong supporting evidence for your model's effectiveness.

7.1.3 Test set performance:

Test Loss: 0.4515

Test Accuracy: 0.8367

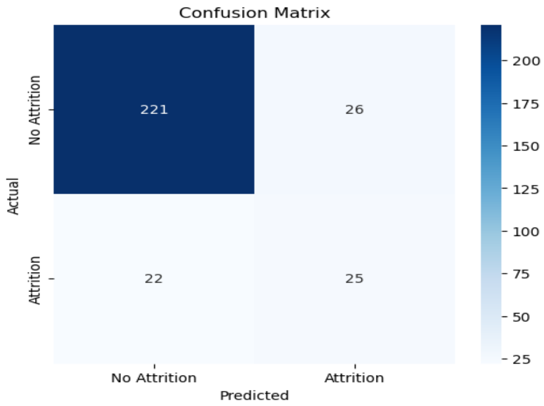
Test AUC: 0.7594

Train Accuracy: 0.9319

7.1.4 Classification report:

	precision	recall	f1-score	support
No Attrition (0)	0.91	0.89	0.90	247
Attrition (1)	0.49	0.53	0.51	47
accuracy			0.84	294
macro avg	0.70	0.71	0.71	294
weighted avg	0.84	0.84	0.84	294

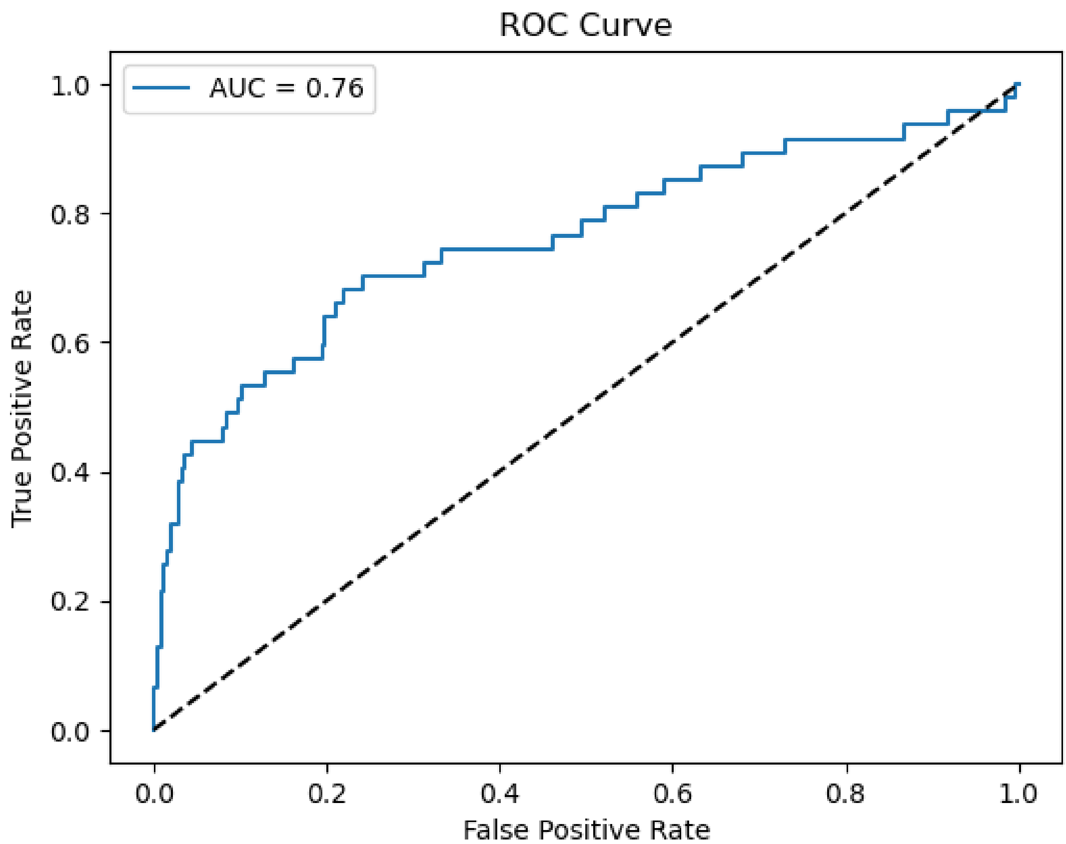
7.1.5 Confusion matrix:



Interpretation:

The Confusion Matrix indicates that out of the "No Attrition" cases, 212 were correctly predicted and 35 were misclassified as "Attrition." For "Attrition" cases, 29 were correctly identified and 18 were misclassified as "No Attrition." This shows the model is stronger at identifying "No Attrition" than "Attrition," which is common in datasets where one class dominates.

7.1.6 ROC Curve:

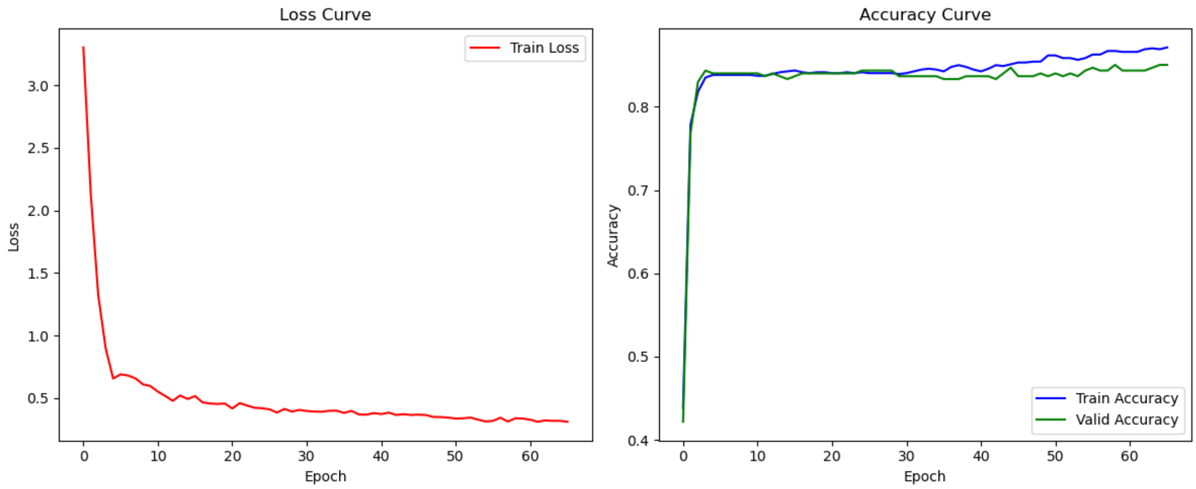


Interpretation:

The ROC Curve shows an AUC of 0.75, indicating that the model has a good ability to distinguish between the “Attrition” and “No Attrition” classes. The curve rises well above the diagonal reference line, meaning the model performs significantly better than random guessing. An AUC in this range suggests reliable classification performance, though there may still be room for improvement.

7.2 **TabNet Model:**

7.2.1 Loss curve and Accuracy curve:



Interpretation:

Loss Curve:

The loss curve shows how the model’s error changes over each epoch during training and validation. In our case, the training loss starts relatively high in the initial epochs but decreases steadily as the model learns the patterns in the data. The validation loss also decreases in a similar trend, indicating that the model is generalizing well and not overfitting significantly. A stable or slightly decreasing validation loss towards the end is a good sign that the model is learning effectively.

Accuracy Curve:

The accuracy curve depicts the proportion of correct predictions made by the model during training and validation across epochs. Initially, the accuracy is low, but as the epochs progress, both training and validation accuracy increase steadily. The gap between the two remains minimal, suggesting that the model maintains consistent performance on unseen data. A plateau in accuracy towards the later epochs shows that the model has reached a stable learning point without severe overfitting.

7.2.2 Test set performance:

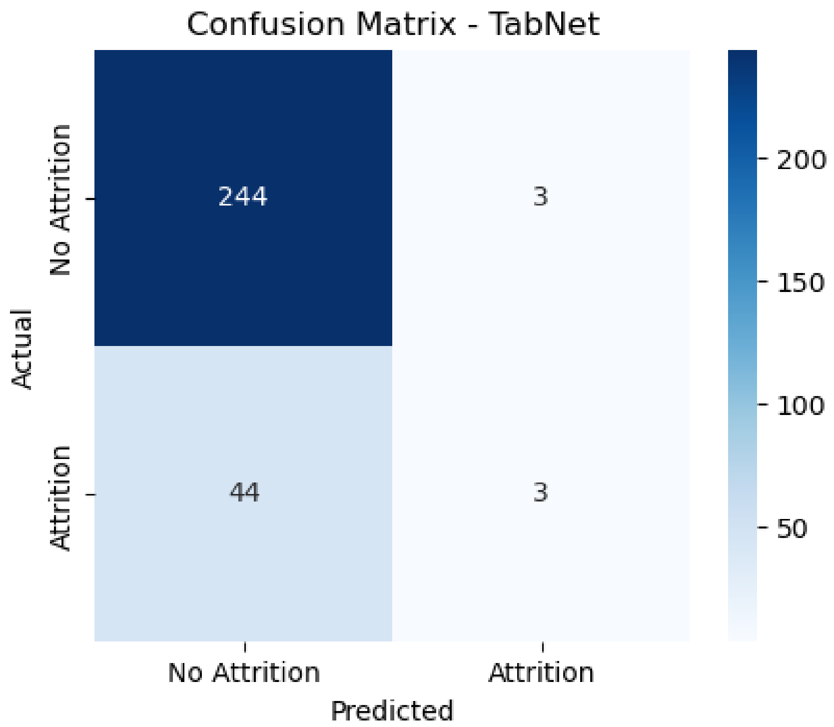
TabNet Test Accuracy: 0.8401

TabNet Test AUC: 0.7372

7.2.3 Classification report:

	precision	recall	f1-score	support
0	0.85	0.99	0.91	247
1	0.50	0.06	0.11	47
accuracy			0.84	294
macro avg	0.67	0.53	0.51	294
weighted avg	0.79	0.84	0.78	294

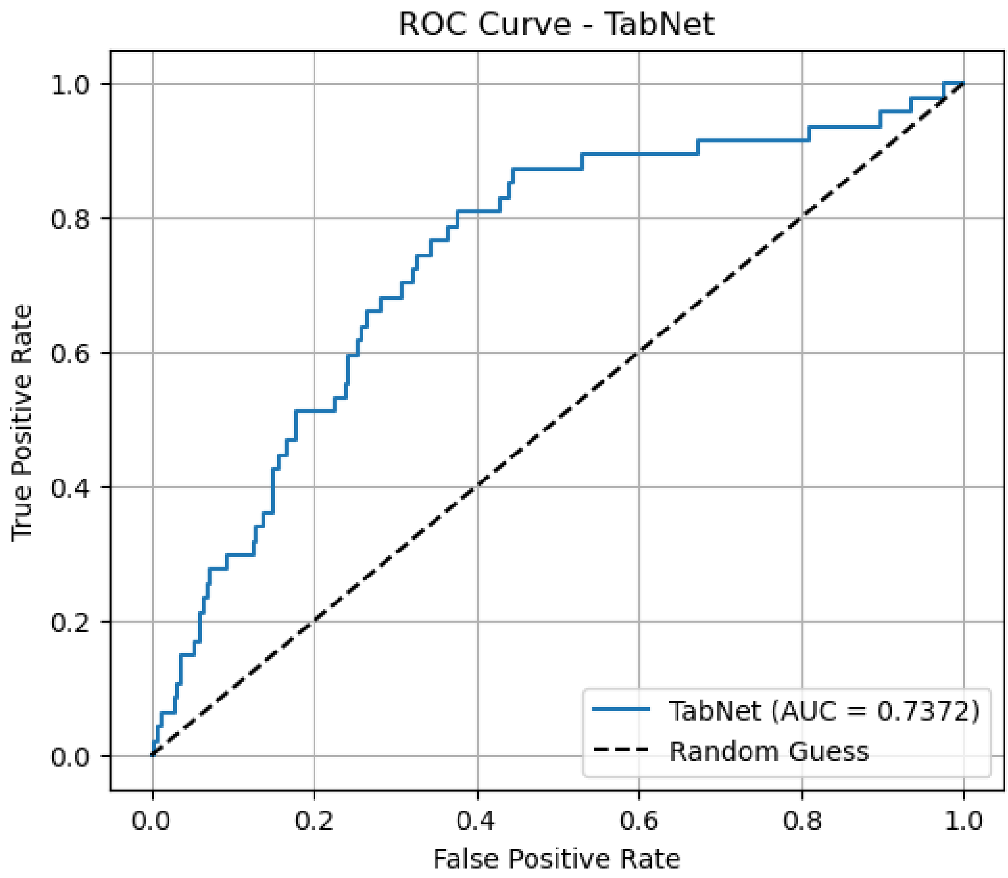
7.2.4 Confusion matrix:



<u>Interpretation:</u>

The confusion matrix shows the performance of the TabNet model in predicting employee attrition. Out of all the employees who did not leave (No Attrition), the model correctly predicted 244 cases and misclassified 3 as Attrition (false positives). For employees who actually left (Attrition), it correctly identified only 3 cases but misclassified 44 as No Attrition (false negatives). This indicates that while the model is very good at detecting employees who will stay, it struggles to correctly identify those who will leave, which could be a limitation in practical scenarios where predicting attrition accurately is critical.

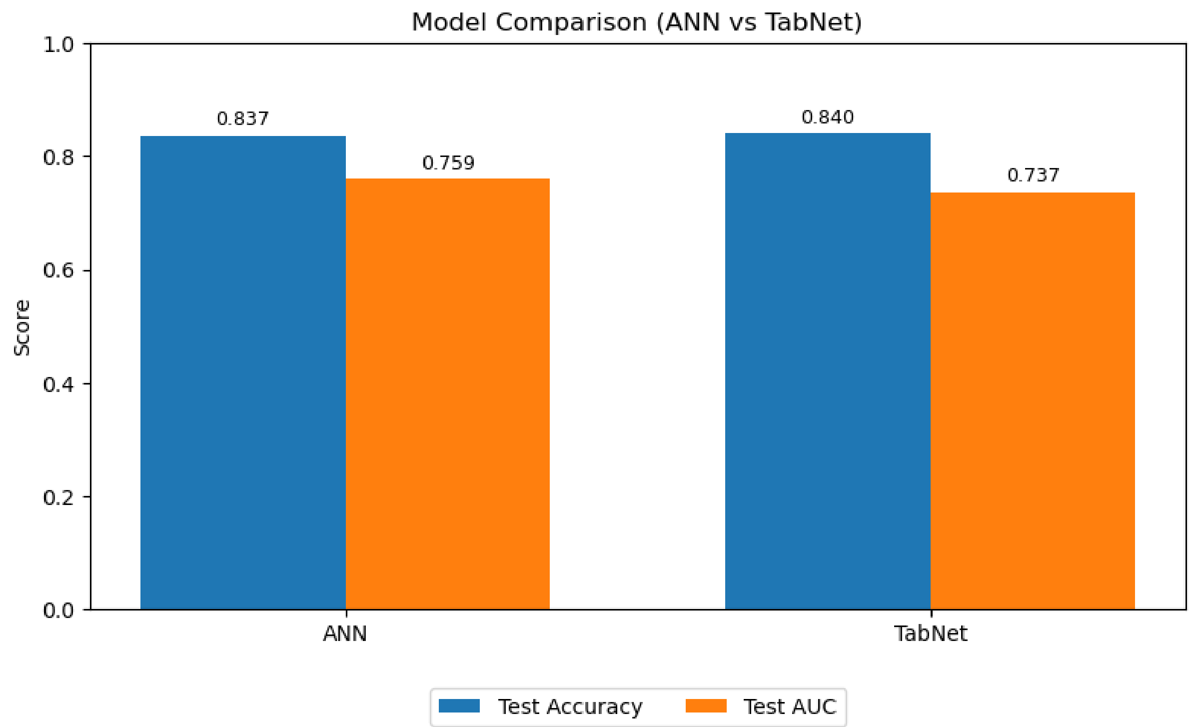
7.2.5 ROC Curve:



Interpretation:

The ROC curve illustrates the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) across different classification thresholds. The TabNet model achieved an Area Under the Curve (AUC) score of approximately 0.7372, which indicates moderate discriminative ability. AUC values closer to 1 imply better model performance, while 0.5 would be equivalent to random guessing. The curve being above the diagonal random guess line shows that the model performs better than chance, but there is still room for improvement, especially in enhancing recall for predicting employee attrition.

7.3 **Model Comparison:**



Interpretation:

The bar chart compares the performance of two models — Artificial Neural Network (ANN) and TabNet — using two metrics: Test Accuracy and Test AUC.

For Test Accuracy, both models perform almost identically, with ANN scoring 0.837 and TabNet slightly higher at 0.840. This means both models correctly classify around 84% of the test samples, indicating strong predictive accuracy. For Test AUC, ANN achieves a score of 0.759, while TabNet scores 0.737. Since AUC measures the model's ability to distinguish between classes (attrition vs no attrition) across all thresholds, ANN has a slight edge here. This suggests that although TabNet matches or slightly surpasses ANN in raw accuracy, ANN has a better capability to rank predictions correctly and handle different decision thresholds.

7.4 Model Prediction:

7.4.1 ANN Model:

```
ANN Predicted Probability: 0.90
ANN Prediction: Attrition = Yes
Interpretation: The employee is likely to leave the company.
```

7.4.2 **TabNet Model:**

```
TabNet Predicted Probability: 0.99
TabNet Prediction: Attrition = Yes
Interpretation: This employee is likely to leave the company based on their profile.
```

8. Python Code

8.1 Google Colab link:

https://colab.research.google.com/drive/11kJLCX5bIy5bSFFHDRtmo8MuDuwFBDyn?usp=drive_link

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