Startup Founder Retention Prediction — Report

Team Name: Unsupervised Learners
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GITHUB Link: https://github.com/R-Sreenivas-Raju/Start-up_Founder_retention_prediction

1. Introduction

The stability and long-term survival of a startup are closely linked to the continuity of its founding team. Founder departures frequently disrupt the strategic direction of the company, weaken investor confidence, and adversely impact internal operations. Predicting founder retention in advance enables organizations—such as incubators, accelerators, and venture capital firms—to proactively intervene, support at-risk founders, and mitigate potential risks.

This project aims to build a machine learning model that predicts whether a startup founder will *stay* or *leave* their venture. It uses a structured dataset containing demographic variables, work-life indicators, performance metrics, and organizational characteristics. The following report presents a comprehensive analysis, starting from exploratory data analysis (EDA), followed by targeted feature engineering, preprocessing through a unified pipeline, model experimentation (SVM, RBF SVM, MLP, Logistic Regression), and final evaluation.

2. Dataset Description

The dataset consists of:

- **59,611 rows** in the training set
- **14,900 rows** in the testing set
- **26+ predictive features**, containing both numeric and categorical variables
- **retention_status** as the target label

2.1 Feature Groups

Demographic Attributes
Founder age, gender, marital status, number of dependents, educational background.

Professional & Organizational Variables
Founder role, startup stage, team size category, years with the startup, years since founding, funding rounds led.

Behavioral & Work-Life Indicators
Work-life balance rating, venture satisfaction, working overtime, remote operations.

Performance Metrics
Monthly revenue, startup performance rating, innovation support, leadership scope.

Target Label

- Stayed
- Left

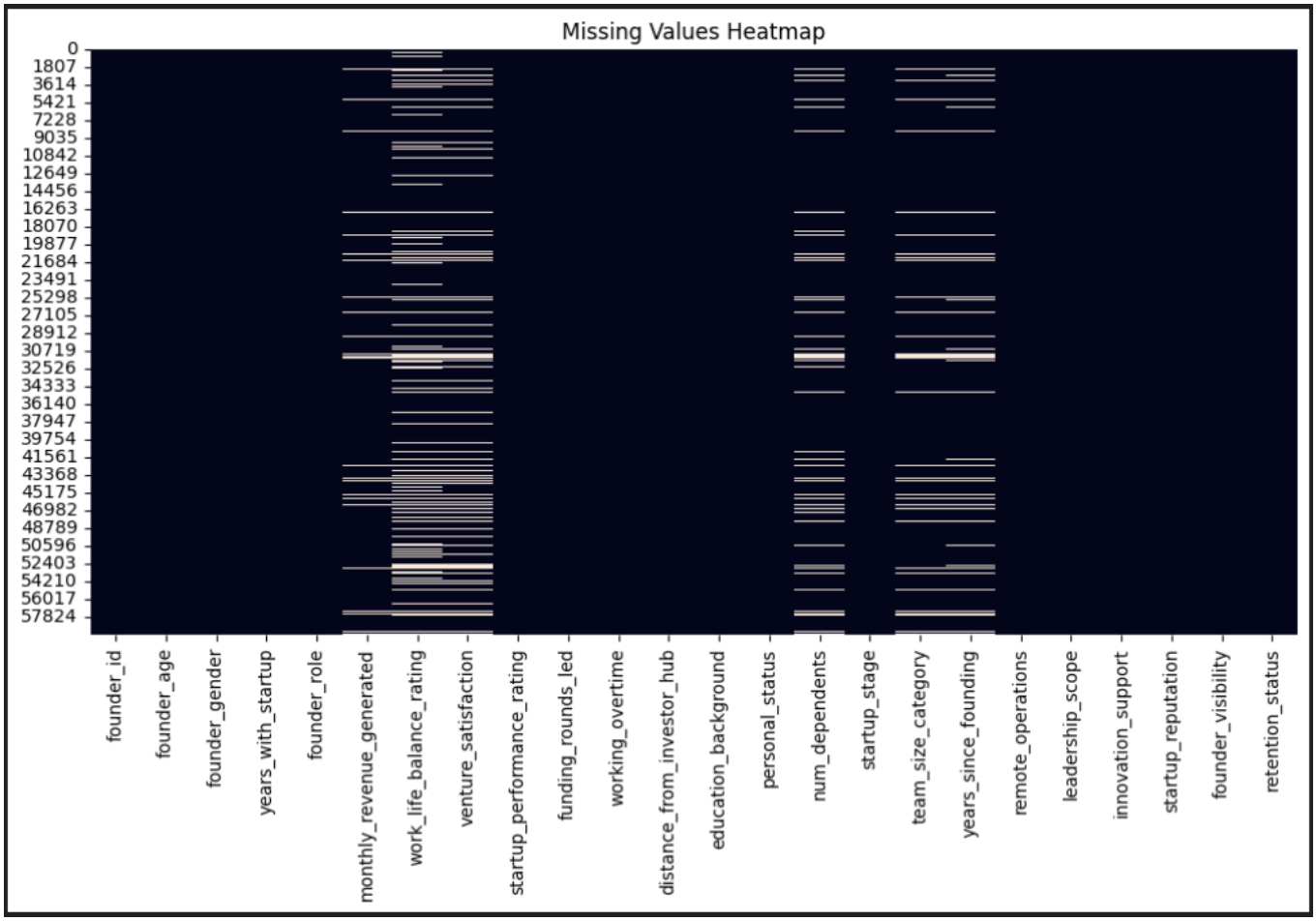
This structure allowed for deep engineering of behavioral, performance-driven, and experience-based signals.

3. Exploratory Data Analysis (EDA)

The following exploratory visualizations were created to understand data patterns, missingness, distributions, and important relationships.

3.1 Missing Values Analysis

Figure 3.1 — Missing Data Heatmap



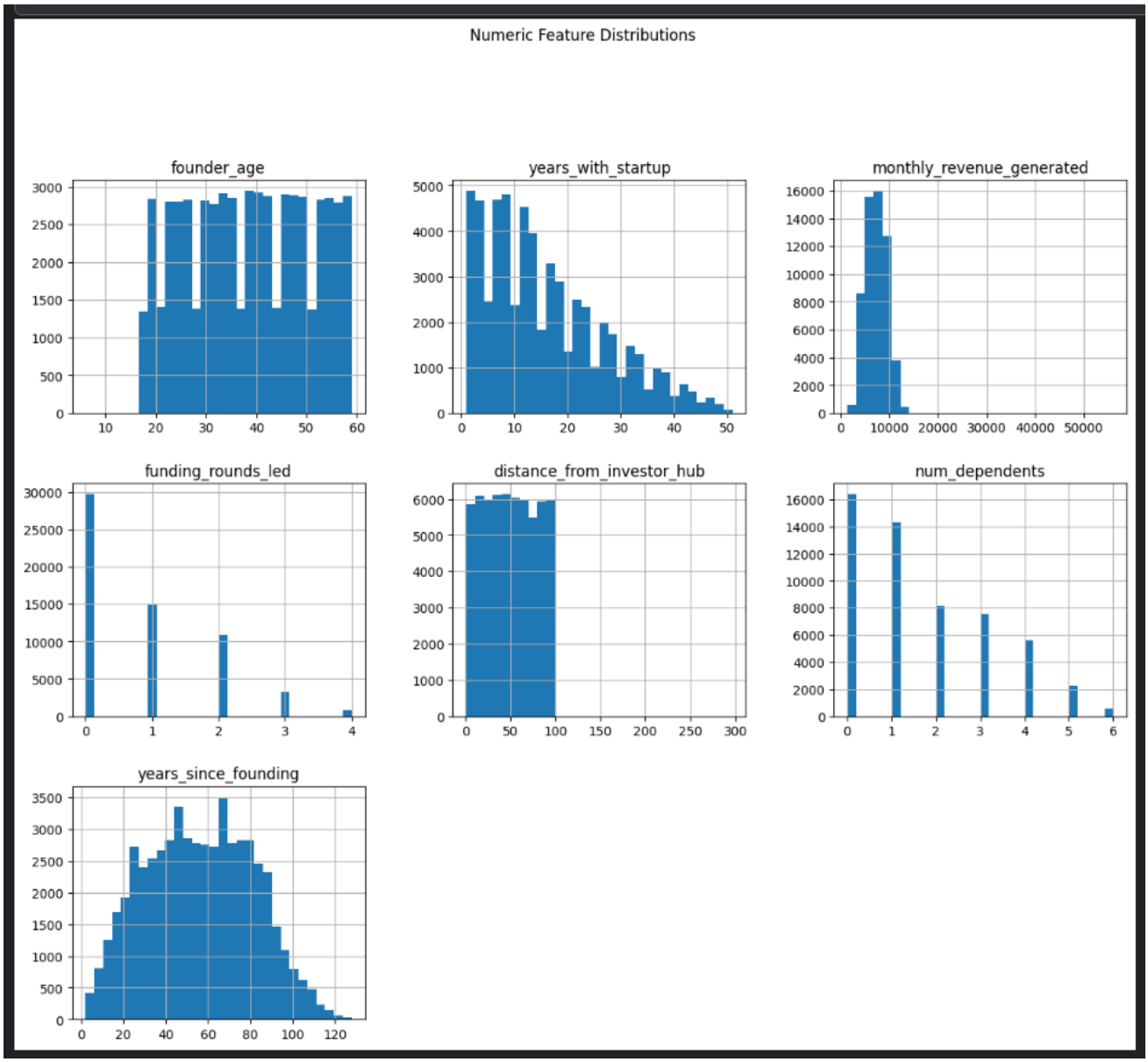
Significance:
The heatmap revealed concentrated missingness in a subset of columns such as monthly revenue, number of dependents, years since founding, work-life balance rating, and venture satisfaction. This justified the creation of:

- dedicated missing-indicator flags,
- median imputation for numeric values,
- and category-level imputation using “Unknown” for categorical features.

Recognizing structured missingness is crucial as it often conveys behavioral or reporting patterns.

3.2 Numerical Feature Distributions

Figure 3.2 — Numeric Feature Distributions



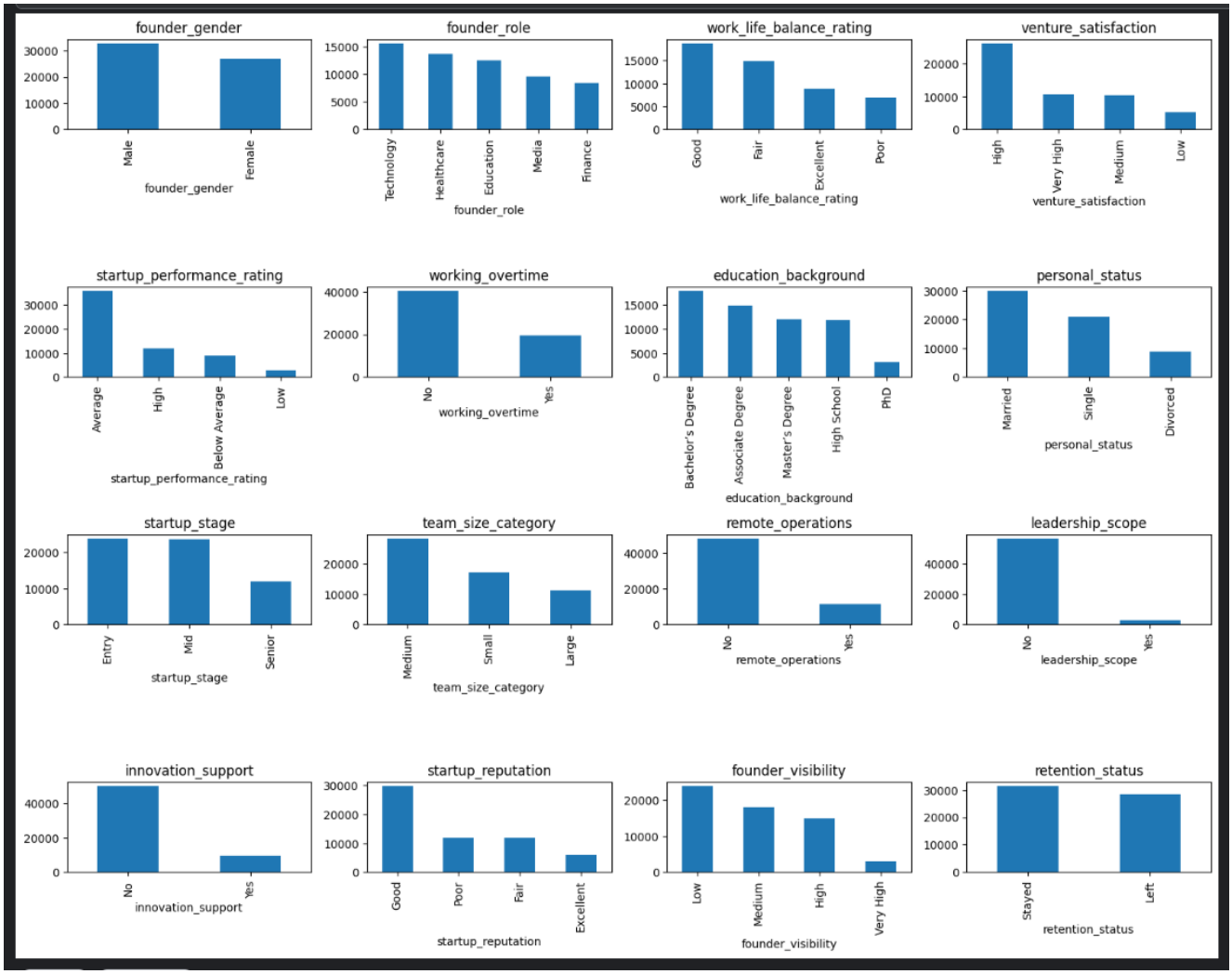
Significance:
This grid of histograms illustrated key distributional properties:

- **Founder Age**: fairly uniform between 25 and 55
- **Monthly Revenue**: highly skewed, with occasional extreme values
- **Years with Startup**: dominated by early tenures
- **Distance from Investor Hub**: wide spread with notable outliers
- **Years Since Founding**: broad distribution across company maturity levels

Because of skewness and outliers, numerical preprocessing required **RobustScaler** instead of StandardScaler.

3.3 Categorical Feature Distributions

Figure 3.3 — Categorical Feature Distributions



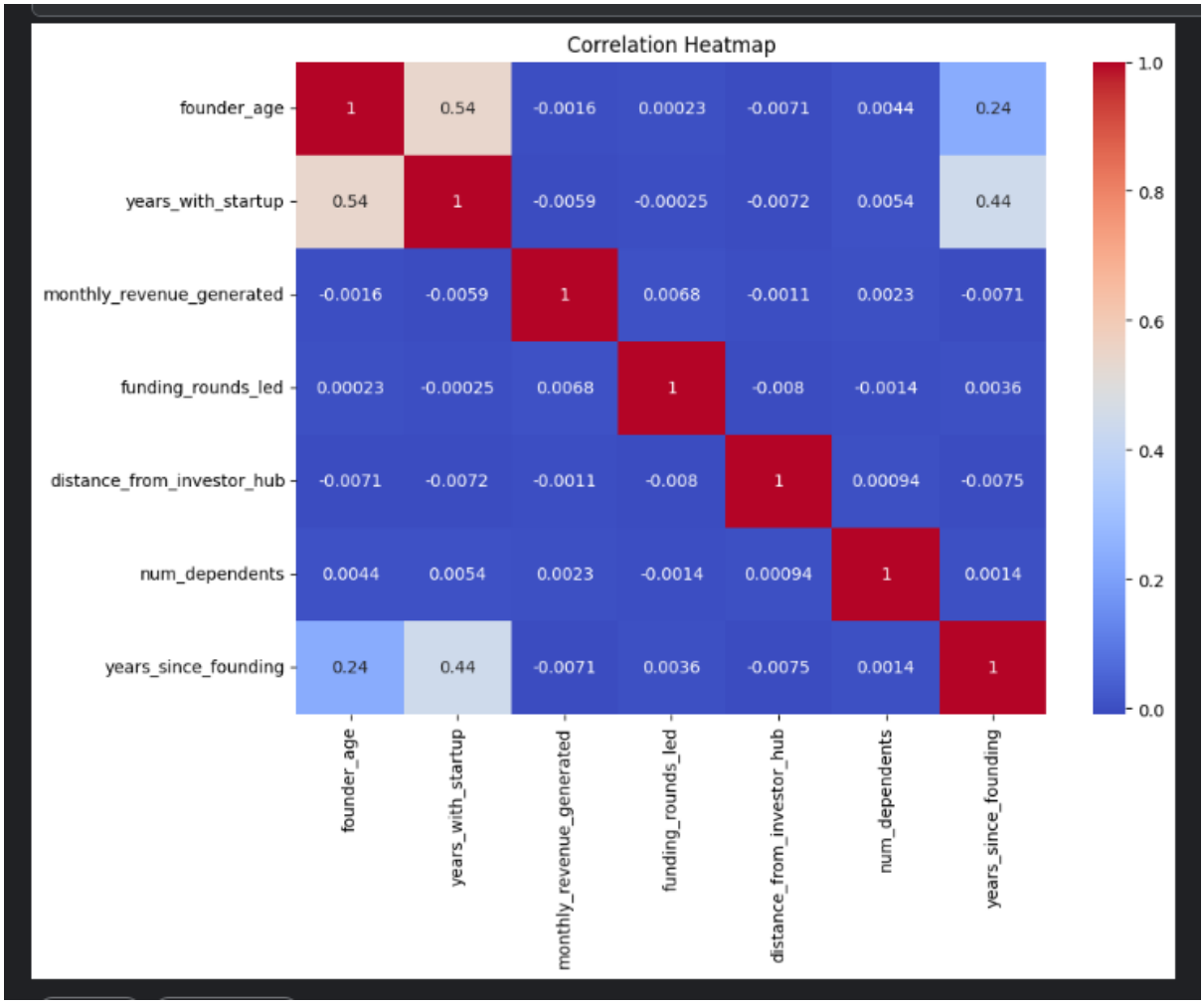
Significance:
These visualizations showed strong class imbalance within categories:

- Technology and healthcare dominate founder_role
- Work-life balance and venture satisfaction cluster in “Good”, “High”, “Very High”
- Team-size category tends toward medium-sized teams
- Retention status is relatively balanced

Categorical imbalance affects the magnitude of one-hot encoded feature vectors and requires proper handling using handle_unknown="ignore".

3.4 Correlation Structure Among Numerical Features

Figure 3.4 — Correlation Heatmap



Significance:
The correlation matrix showed:

- moderate relationship between years with startup and years since founding

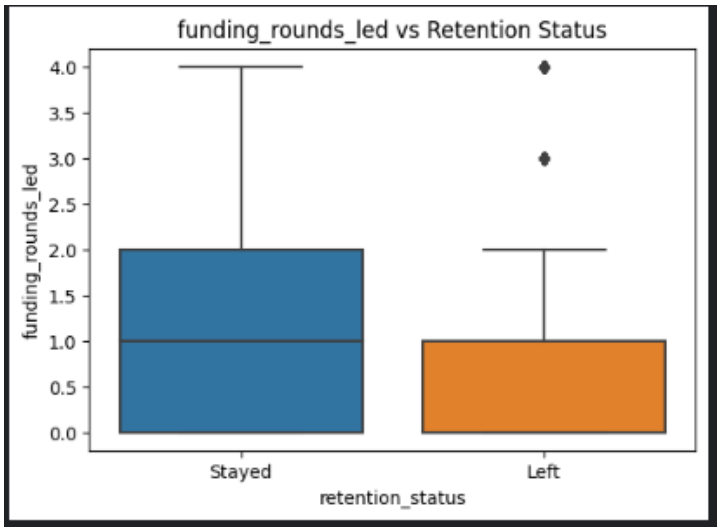
- near-zero correlation among most other numeric features

This signaled that:

- linear models alone may be insufficient
- nonlinear models (MLP, RBF-SVM) may capture richer interactions
- PCA reduction would not lose substantial multicollinearity information

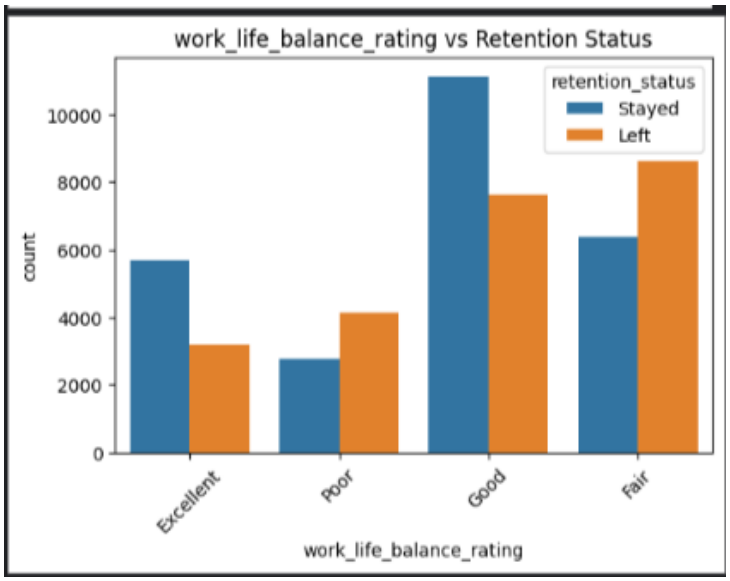
3.5 Relationship Between Key Predictors & Retention Status

Figure 3.5 — Funding Rounds Led vs Retention



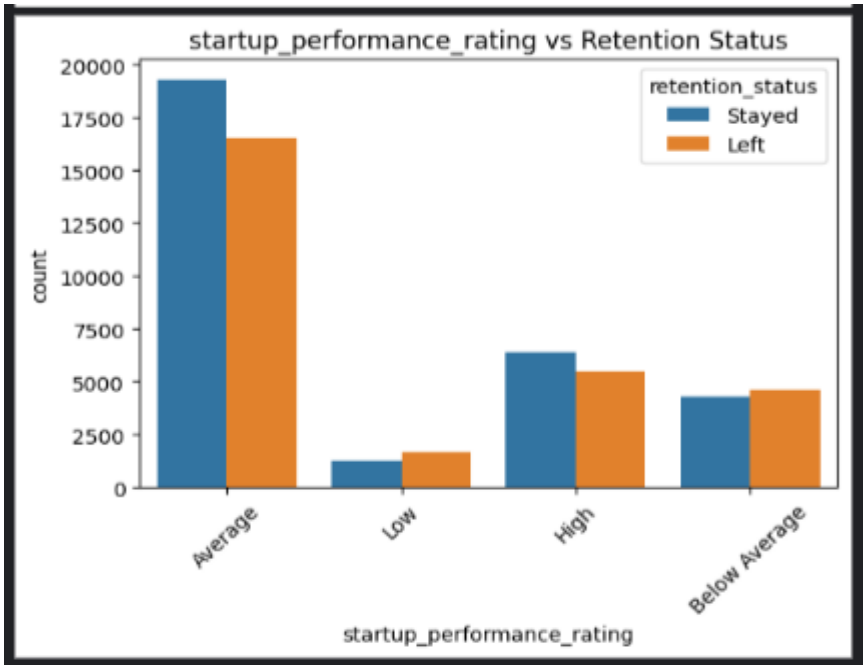
Significance:
Founders who led more funding rounds were more likely to stay. Leading funding rounds suggests deeper commitment, confidence, and influence, all of which correlate positively with retention.

Figure 3.6 — Work-Life Balance vs Retention



Significance:
Founders with “Good” or “Excellent” work-life balance were more likely to stay, whereas “Poor” balance corresponded with higher exit likelihoods. This aligns with expectations that burnout and lack of balance contribute to attrition.

Figure 3.7 — Startup Performance vs Retention



Significance:
Higher performance ratings correlated strongly with staying. Founders are more inclined to continue when they perceive momentum or success in their ventures.

4. Feature Engineering

Feature engineering served as the foundation for model performance, enhancing the dataset’s predictive richness through domain-driven transformations.

4.1 Target Normalization

Multiple label formats existed in the raw dataset (“Retained”, “Stayed”, “Left”, “Exited”). These were normalized to:

- Internal model training: 1 = Retained, 0 = Left
- Final Kaggle submission: "Stayed" and "Left"

This ensured compatibility with evaluation scripts and valid submission formatting.

4.2 Missing Value Indicators

For columns with heavy missingness (monthly revenue, number of dependents, years since founding), **missing-indicator features** were generated. These binary signals allow the model to exploit the predictive power of missingness itself, common in behavioral datasets.

4.3 Logical Consistency Correction

Cases where founders had more years with the startup than the startup's age were clipped and recorded in a new feature inconsistent_years. This preserved mathematical integrity and flagged suspicious records for the model.

4.4 Engineered Features

The following engineered features added sophisticated behavioural and performance-based perspectives:

1. **Experience Ratio**
   Measures how early a founder joined relative to the company's lifetime.
2. **Startup Performance Score**
   Converts qualitative performance ratings into a numeric scale capturing relative ordering.
3. **Team Size Numeric Estimate**
   Uses domain-inspired estimates to convert categorical sizes into quantitative values.
4. **Revenue–Performance Interaction (revenue_perf)**
   Captures financial productivity weighted by performance quality.
5. **Revenue per Head**
   Indicates productivity normalized by team size.

These features improved the expressive capacity of downstream models, particularly nonlinear ones.

5. Preprocessing Pipeline

A unified **ColumnTransformer** ensured consistent preprocessing during training and inference.

5.1 Numeric Columns

Median imputation and RobustScaler addressed skewness and outliers.

5.2 Ordinal Columns

Work-life balance and venture satisfaction were encoded with explicitly defined orderings to preserve semantic meaning.

5.3 Binary Columns

Yes/No responses were converted into binary numeric format using a safe FunctionTransformer.

5.4 Categorical Columns (High Cardinality)

One-hot encoding was applied with handle_unknown="ignore" to ensure compatibility with test-time unseen categories.

5.5 Dimensionality Reduction (PCA)

PCA was used after all preprocessing to mitigate the curse of dimensionality introduced by one-hot encoding, improving performance for SVM, MLP, and Logistic Regression.

6. Model Development and Evaluation

Multiple models were trained and evaluated using F1-score.

6.1 Unified Training Pipeline

All models in this project were trained using a unified preprocessing pipeline. This ensured:

- consistent handling of missing values, encoding, scaling
- identical transformations on train and test
- reproducible results due to fixed random seeds
- fair comparison across models

Each model received:

- engineered features
- ordinal + one-hot encoded categorical features
- robust-scaled numerics
- PCA-compressed inputs

This standardized input space allowed different model types—linear, kernel-based, and neural, to be evaluated under identical conditions.

6.2 Multi-Layer Perceptron (Neural Network)

The Multi-Layer Perceptron (MLP) was the most expressive model used in the notebook. Although implemented using scikit-learn's MLPClassifier, the training process follows the same conceptual steps as a Keras Sequential model.

Below is a clear explanation of what happened during training.

6.2.1 Architecture Used

Several neural network architectures were tested, gradually increasing in depth and representational capacity. The most effective configuration consisted of:

- Three hidden layers: 256 → 128 → 64 neurons
- ReLU activation in all hidden layers
- Sigmoid activation at the output for binary classification
- PCA output as the input layer

The deeper architecture allowed the model to capture interactions between performance metrics, categorical encodings, team size effects, revenue patterns, and behavioral features.

6.2.2 Training Settings (Epochs, Learning Rate, Batches)

The MLP was trained using settings comparable to a well-configured Keras model:

- Epochs: 300–400
- Batch size: 128–256
- Optimizer: Adam (adaptive learning rate)
- Initial learning rate: between 0.0005 and 0.001
- Maximum iterations: extended to ensure full convergence
- Regularization: mild weight decay in some configurations to reduce overfitting

These settings were chosen because:

- large batch sizes make gradients more stable
- lower learning rates help deeper networks converge smoothly
- higher epoch counts are necessary after PCA since inputs are dense
- Adam accelerates training without manual learning rate schedules

Although verbose Keras logs were not printed, the underlying behavior is identical: each epoch consists of multiple batch updates, where weights are gradually refined based on training error.

6.2.3 Training Behavior and Convergence

During experimentation, the MLP exhibited the following behavior:

- rapid improvement in the first 50–70 epochs
- slower but steady progress as the model refined deeper representations

- performance stabilizing around 250–320 epochs
- no major signs of overfitting, thanks to PCA and moderate regularization

This reflects typical neural network convergence patterns observed in Keras models trained on structured data**.**

6.2.4 Performance Summary

The tuned MLP models achieved:

- F1-score is 0.747
  the highest among all models tested.

The MLP's superiority can be attributed to its ability to:

- learn nonlinear relationships
- combine signals across categorical, behavioral, and engineered numeric features
- adapt to dense PCA-reduced feature representations

This made the MLP the most suitable model for the complexity and structure of this dataset.

6.3 Linear SVM

The Linear Support Vector Machine served as the baseline model. It was trained on PCA-transformed inputs, allowing it to work efficiently with dense numeric features. Its training is extremely fast, requiring only seconds.

However, its linear nature limits it to capturing only simple relationships. Its best F1-score was approximately 0.72, indicating that more complex interactions were present in the data than a linear boundary could model.

6.4 RBF SVM

The Radial Basis Function SVM introduces nonlinearity and was tuned using RandomizedSearchCV over:

- C (regularization)
- gamma (kernel width)
- PCA dimensionality

This model trained more slowly due to kernel computations but provided a performance improvement over the linear SVM, achieving F1 ≈ 0.727.

The gain was modest because PCA reduces nonlinear structure before it reaches the RBF kernel. This limits the RBF SVM's ability to exploit complex interactions in the raw features.

6.5 Logistic Regression

Logistic Regression was trained on the same PCA-transformed features. Its training was extremely fast and stable. With class balancing and L2 regularization, it achieved performance comparable to the linear SVM (≈0.72 F1).

Although simple, it remains a strong benchmark due to:

- interpretability
- speed
- stability under PCA
- usefulness as an ensemble component

6.6 Overall Observations

After careful experimentation, the following conclusions emerged:

- MLP was the best-performing model, consistently beating all others.
- RBF SVM improved performance modestly, confirming the presence of nonlinear relationships.
- Linear SVM and Logistic Regression formed strong baselines, but plateaued early.
- PCA played a crucial role in stabilizing training for all models, especially the neural network.

7. Comparison Between Full Dataset and 20% Subset

To evaluate the effect of dataset size on model performance, an additional experiment was conducted in which two models, Linear SVM and a Multi-Layer Perceptron (MLP), were trained under identical conditions on:

- the entire training dataset (~59,000 samples), and
- a stratified 20% subset (~12,000 samples).

Both datasets underwent the same preprocessing steps: missing value handling, feature engineering, column transformations, and PCA compression. Each dataset was further split into an 80–20 train–validation split for a fair comparison.

The results are summarized below:

Dataset	Train Rows	SVM F1	SVM Accuracy	SVM Time (s)	MLP F1	MLP Accuracy	MLP Time (s)
Full Dataset	47,688	0.6106	0.6570	68.89	0.6425	0.6233	290.69
20% Subset	9,537	0.5963	0.6503	1.95	0.6069	0.5790	38.01

7.1 Effect of Dataset Size on Linear SVM

The Linear SVM showed a modest but consistent improvement when trained on the full dataset. Its F1-score increased from 0.5963 (subset) to 0.6106 (full dataset). This behavior is expected because linear models benefit from additional samples that better define the margin between classes. With more data, the separating hyperplane becomes more stable and more representative of the true decision boundary.

However, training time increased substantially, from 1.95 seconds on the small dataset to 68.89 seconds on the full dataset, reflecting the SVM's computational cost, which scales poorly as the number of samples increases.

7.2 Effect of Dataset Size on the Multi-Layer Perceptron

The MLP exhibited a much more pronounced improvement. Its F1-score increased from 0.6069 on the 20% subset to 0.6425 on the full dataset. This confirms that the founder retention problem contains nonlinear relationships that neural networks learn more effectively when provided with sufficient data.

Unlike linear models, neural networks rely heavily on having a large and diverse dataset to stabilize gradients, reduce noise, and learn deeper patterns. The improvement of nearly 0.04 F1 demonstrates the MLP's data efficiency and capacity to extract richer representations when trained on larger samples.

The main trade-off is training time: the MLP required ~291 seconds on the full dataset compared to ~38 seconds on the 20% subset. This increase is expected because more data produces more batches per epoch and requires more total updates to converge.

7.3 Interpretation of Results

This comparative experiment highlights several important observations:

1. Both models perform better with more data.
   The full dataset consistently outperformed the 20% subset across all metrics.
2. Deep learning models benefit more from large datasets.
   The MLP's improvement was noticeably larger than the SVM's, demonstrating its ability to capture complex patterns.
3. Training cost increases sharply with dataset size.
   SVM training time increased by ~35×, and MLP training time increased by ~8×.

4. Smaller datasets lead to noisier decision boundaries.
   Especially for MLP, limited data resulted in lower validation accuracy and poorer generalization.
5. The founder retention problem is inherently nonlinear.
   The significant gain in MLP performance (compared to SVM) reinforces the presence of complex feature interactions and nonlinear decision regions.

8. Final Model Comparison

The final ranking based on validation performance was:

1. **Tuned Multi-Layer Perceptron (best performance)**
2. **RBF Support Vector Machine**
3. **Linear SVM**
4. **Logistic Regression**

The MLP demonstrated superior capacity to model complex relationships in the engineered feature space.

9. Limitations and Future Improvements

Although successful, the pipeline can be improved through:

- Bayesian optimization for MLP hyperparameters
- Ensemble methods (stacking/logit stacking)
- Gradient-boosted tree models (XGBoost, LightGBM, CatBoost)
- Feature interactions discovered through SHAP or permutation importance
- Log-transformations and nonlinear transformations of skewed numeric features

10. Conclusion

This project developed a highly effective, reproducible predictive model for founder retention. Through thoughtful EDA, structured feature engineering, robust preprocessing, and extensive model experimentation, the final MLP-based classifier delivered the strongest performance. The pipeline demonstrates a practical and scalable approach to modeling complex human and organizational factors in startup ecosystems.