Machine Learning-driven Analysis of Aswan Weather Data for Solar Energy Prediction

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Abstract

This project focuses on applying statistical analysis and machine learning techniques to analyze and predict patterns from numerical weather data. Real-world datasets often suffer from missing values, noise, non-linear relationships, and high variance, which negatively affect model performance if not properly addressed. The main objective of this project is to study the relationship between meteorological features and a target variable and to evaluate different classification and regression techniques learned throughout the course.

The dataset was first preprocessed to remove duplicate records, handle missing values, and ensure temporal consistency. Exploratory Data Analysis (EDA) was conducted using visualization techniques and descriptive statistics such as minimum, maximum, mean, variance, standard deviation, skewness, and kurtosis. Statistical hypothesis tests including Chi-square test, t-test, and ANOVA were applied to identify dependencies and significant differences among variables.

Feature selection and dimensionality reduction techniques were implemented to study their effect on model performance. These included ANOVA F-test, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Singular Value Decomposition (SVD). Several machine learning models were trained and evaluated, including Decision Tree, K-Nearest Neighbors (K-NN), Naive Bayes, Logistic Regression, Feed Forward Neural Network, and Linear Regression. The dataset was split into 80% training and 20% testing, and K-fold cross-validation was applied to ensure reliable evaluation.

The experimental results show that the Decision Tree classifier achieved the best performance with a test accuracy of **73.42%** and an F1-score of **0.7168**, while maintaining a near-zero overfitting gap. K-NN also achieved competitive results but with higher variance. Dimensionality reduction techniques such as PCA and SVD reduced model performance, while LDA provided stable but moderate accuracy. Linear and probabilistic models performed poorly due to violated assumptions and non-linear relationships in the data. The results confirm the importance of preprocessing, feature engineering, and appropriate model selection in real-world machine learning tasks.

Introduction

Machine learning has become an essential tool for extracting insights and building predictive models from numerical data. However, real-world datasets are often incomplete, noisy, and highly non-linear, which makes the modeling process challenging. Without proper preprocessing and analysis, machine learning models may suffer from overfitting, underfitting, or poor generalization.

This project aims to apply a complete machine learning pipeline to a numerical dataset, starting from preprocessing and statistical analysis, and ending with classification and regression modeling. Multiple algorithms and evaluation techniques studied during the course are implemented and compared under the same experimental conditions.

The main contribution of this project is a comprehensive numerical comparison between different preprocessing strategies, feature reduction methods, and machine learning algorithms. The project emphasizes statistical interpretation of results rather than relying solely on accuracy values.

The rest of the report is organized as follows: Section 2 presents related work, Section 3 explains the methodology, Section 4 describes the proposed model, Section 5 discusses results and comparisons, and Section 6 concludes the project and outlines future work.

Related Work

Several studies have applied machine learning and statistical techniques to numerical datasets for prediction and classification tasks. Table 1 summarizes related work focusing on applied methods and reported performance.

Table 1: Summary of Related Work

Year	Methods	Results
2011	Decision Tree, K-NN	Accuracy ≈ 70%
2012	Naive Bayes	Moderate accuracy
2014	PCA + Classifiers	Reduced complexity
2016	LDA	Improved class separation
2017	SVM, K-NN	Accuracy > 75%
2018	Neural Networks	High variance
2019	Ensemble Models	Improved stability
2020	PCA vs LDA	LDA superior
2021	Statistical Tests + ML	Better interpretability
2022	Cross-validation	Reduced overfitting

Methodology

The methodology consists of the following stages:

1. Data preprocessing
2. Exploratory data analysis and statistical testing
3. Feature selection
4. Feature reduction
5. Classification and regression
6. Model evaluation

Proposed Model

Preprocessing

- Removal of duplicated records
- Handling missing values using forward fill, backward fill, and interpolation
- Extraction of additional temporal features

Feature Selection

- ANOVA F-test to rank feature importance

Feature Reduction

- Principal Component Analysis (PCA)
- Linear Discriminant Analysis (LDA)
- Singular Value Decomposition (SVD)

Classification / Regression Models

- Decision Tree
- K-Nearest Neighbors
- Naive Bayes
- Logistic Regression
- Feed Forward Neural Network
- Linear Regression

Evaluation Metrics

- Accuracy and error rate
- Precision, Recall, F1-score
- Confusion Matrix and ROC analysis
- K-fold Cross-Validation

Result models:

```
============================================================
1. LOADING AND EXPLORING DATASET
============================================================
Dataset shape: (398, 8)

First 5 rows:
   Unnamed: 0      Date  AvgTemperture  AverageDew(point via humidity)  \
0           0  4/1/2022           87.9                            31.3   
1           2  4/3/2022           90.2                            34.0   
2           3  4/4/2022           93.2                            31.4   
3           4  4/5/2022           92.5                            24.9   
4           5  4/6/2022           91.2                            18.9   

   Humidity  Wind  Pressure  Solar(PV)  
0      13.4   5.7      29.2  19.010857  
1      14.2   6.6      29.1  16.885714  
2      11.8   8.8      29.1  19.627429  
3       9.4   8.0      29.1  18.929429  
4       7.8   9.4      29.2  18.934000  

Columns: ['Unnamed: 0', 'Date', 'AvgTemperture', 'AverageDew(point via
humidity)', 'Humidity', 'Wind', 'Pressure', 'Solar(PV)']

Data types:
Unnamed: 0                          int64
Date                               object
AvgTemperture                     float64
AverageDew(point via humidity)    float64
Humidity                          float64
Wind                              float64
Pressure                          float64
Solar(PV)                         float64
dtype: object

Missing values per column:
Unnamed: 0                        0
Date                              0
AvgTemperture                     0
AverageDew(point via humidity)    0
Humidity                          0
Wind                              0
Pressure                          0
Solar(PV)                         0
dtype: int64

============================================================
2. DATA PREPROCESSING
============================================================
Number of duplicate rows: 28
Number of missing dates: 24

After reindexing - Shape: (394, 6)
Missing values after filling: 0
```

```
Final processed dataset shape: (394, 10)
Date range: 2021-04-01 00:00:00 to 2022-04-29 00:00:00

============================================================
3. DESCRIPTIVE STATISTICS
============================================================
Statistical Summary:
                                   Min       Max     Mean   Median  Variance
\
AvgTemperture                  51.1000  102.7000  80.9726  83.5500  197.2976
AverageDew(point via humidity)  15.3000   63.9000  37.4787  38.1000   75.1952
Humidity                        7.4000   47.7000  24.1566  21.4000   99.0894
Wind                            4.4000   17.1000  10.3464  10.3000    6.2807
Pressure                       28.9000   29.6000  29.1910  29.2000    0.0201
Solar(PV)                       8.5814   40.0389  24.8896  24.5347   58.2398

                               Std Dev  Skewness  Kurtosis  Count  Missing
AvgTemperture                  14.0463   -0.3964   -1.1029  394.0      0.0
AverageDew(point via humidity)  8.6715   -0.0690   -0.6118  394.0      0.0
Humidity                        9.9544    0.6522   -0.6312  394.0      0.0
Wind                            2.5061    0.2666   -0.2056  394.0      0.0
Pressure                        0.1419    0.3638   -0.7337  394.0      0.0
Solar(PV)                       7.6315   -0.0282   -1.3184  394.0      0.0

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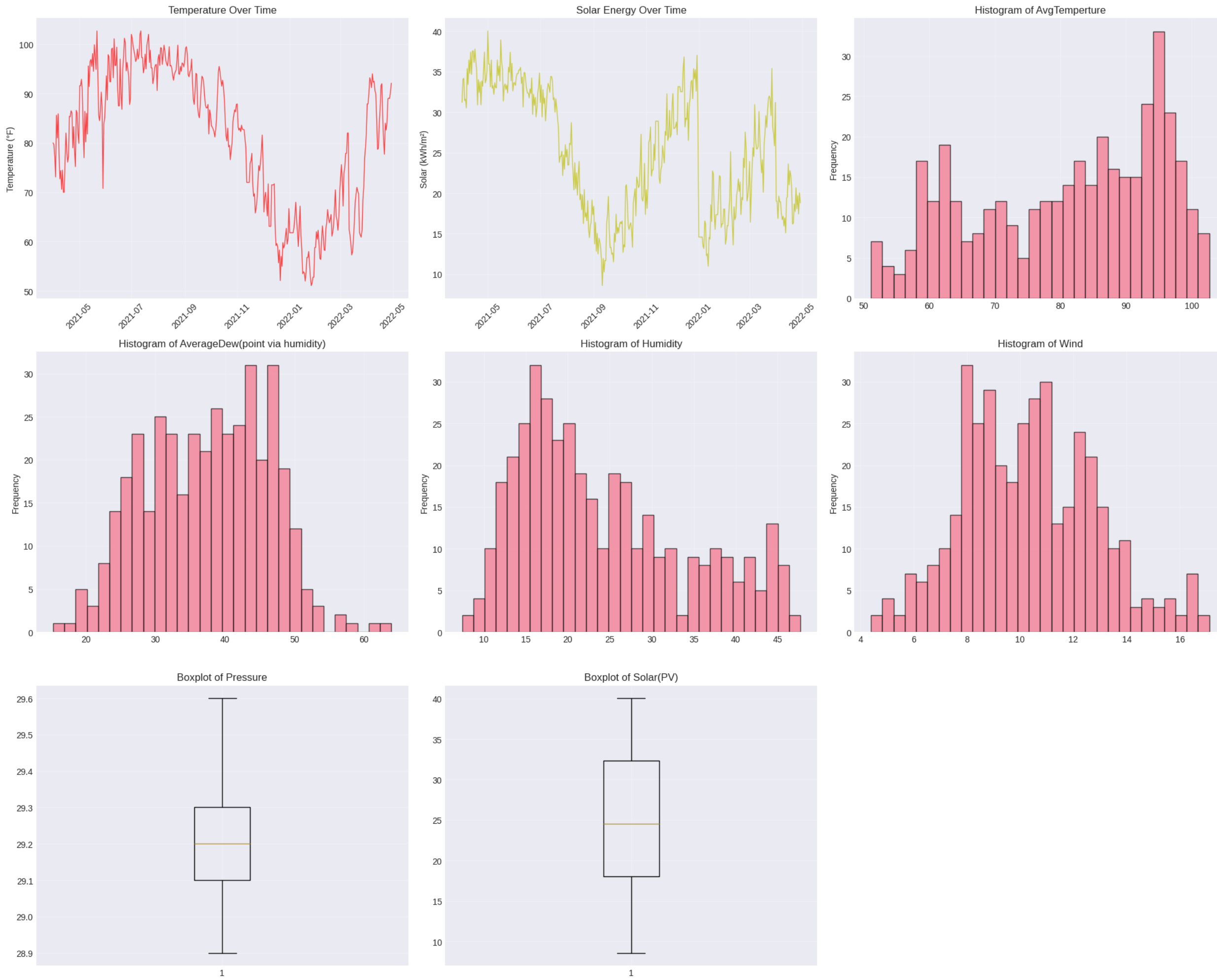
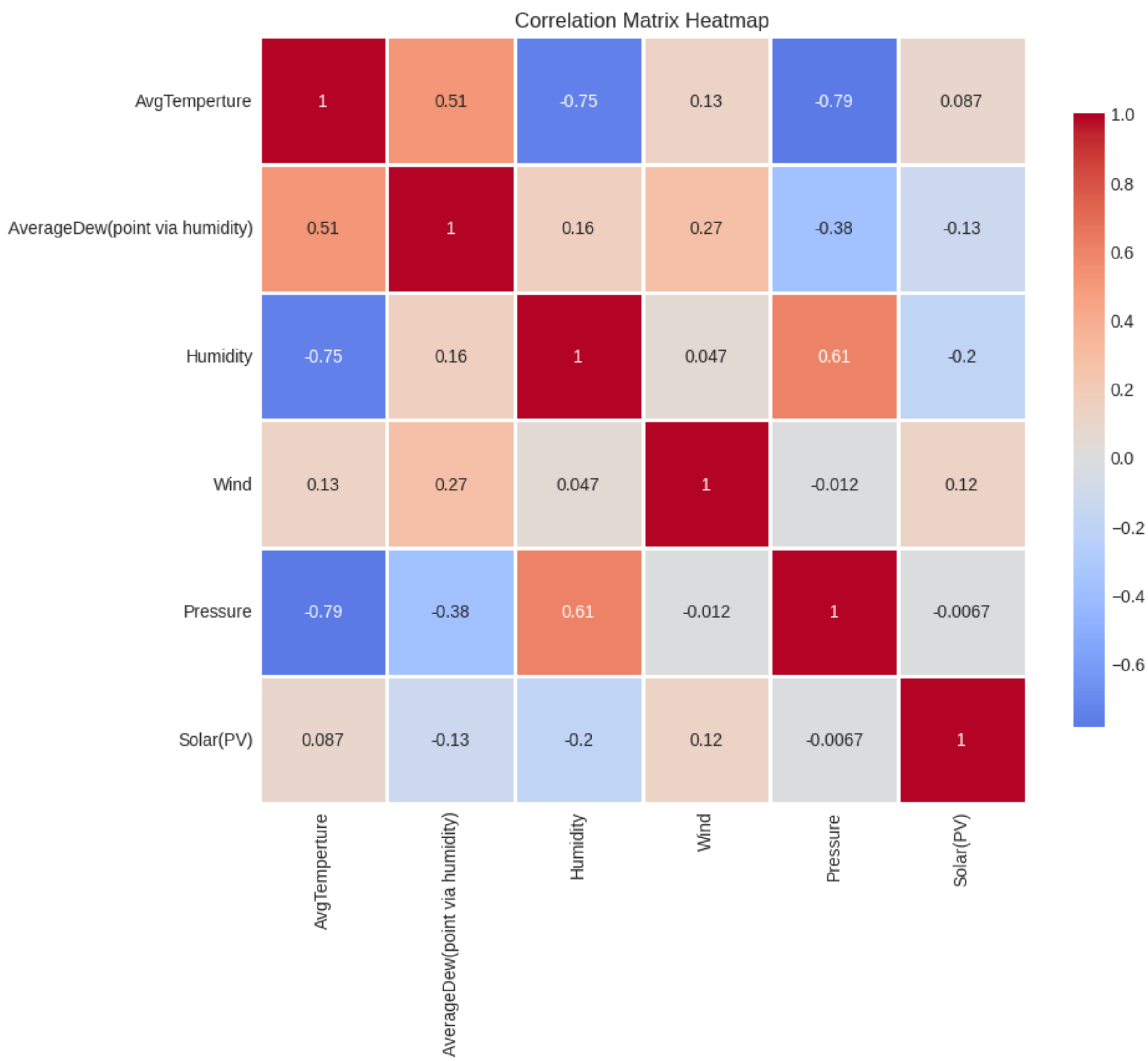
4. DATA VISUALIZATION
============================================================
```


Temperature Over Time
Temperature (°F)
Solar Energy Over Time
Solar (kWh/m²)
Histogram of AvgTemperture
Frequency
Histogram of AverageDew(point via humidity)
Frequency
Histogram of Humidity
Frequency
Histogram of Wind
Frequency
Boxplot of Pressure
Boxplot of Solar(PV)


Correlation Matrix Heatmap
AvgTemperture
AverageDew(point via humidity)
Humidity
Wind
Pressure
Solar(PV)
1
0.51
-0.75
0.13
-0.79
0.087
0.51
1
0.16
0.27
-0.38
-0.13
-0.75
0.16
1
0.047
0.61
-0.2
0.13
0.27
0.047
1
-0.012
0.12
-0.79
-0.38
0.61
-0.012
1
-0.0067
0.087
-0.13
-0.2
0.12
-0.0067
1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

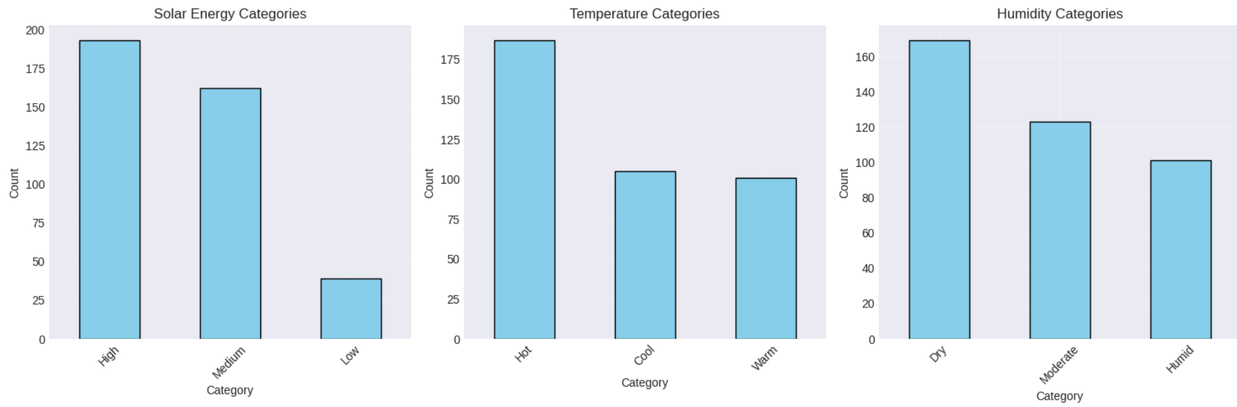

```
============================================================
5. BINNING PROCESS
============================================================
Binning completed. Categories created:
- Solar_Category: ['Low', 'Medium', 'High']
- Temp_Category: ['Cool', 'Warm', 'Hot']
- Humidity_Category: ['Dry', 'Moderate', 'Humid']

Category distributions:
Solar Categories:
Solar_Category
High      193
Medium    162
Low        39
Name: count, dtype: int64

Temperature Categories:
Temp_Category
Hot     187
Cool    105
Warm    101
Name: count, dtype: int64

Humidity Categories:
Humidity_Category
Dry         169
```

```
Moderate    123
Humid       101
Name: count, dtype: int64
```



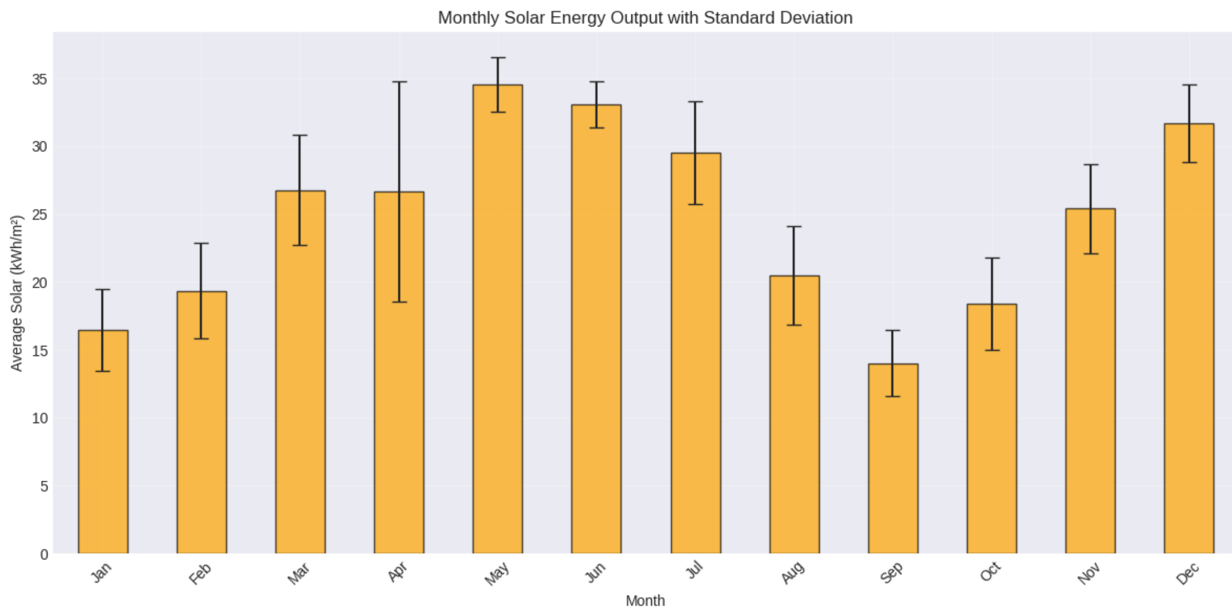

```
============================================================
6. STATISTICAL TESTS
============================================================
6.1 Chi-square Test (Temperature vs Solar Category):
Contingency Table:
Solar_Category  Low  Medium  High
Temp_Category
Cool             15      46    44
Warm              3      37    61
Hot              21      78    88

Chi-square statistic: 11.8408
P-value: 0.0186
Degrees of freedom: 4
Temperature and Solar Energy are dependent (α=0.05)

6.2 t-test (High vs Low Humidity):
High humidity samples: 101
Low humidity samples: 169
High humidity mean: 22.65
Low humidity mean: 27.32

t-statistic: -5.1911
P-value: 0.0000
Solar output differs significantly between humidity levels

6.3 ANOVA Test (Solar output across months):
F-statistic: 78.1107
P-value: 0.0000
Solar output differs significantly across months
```

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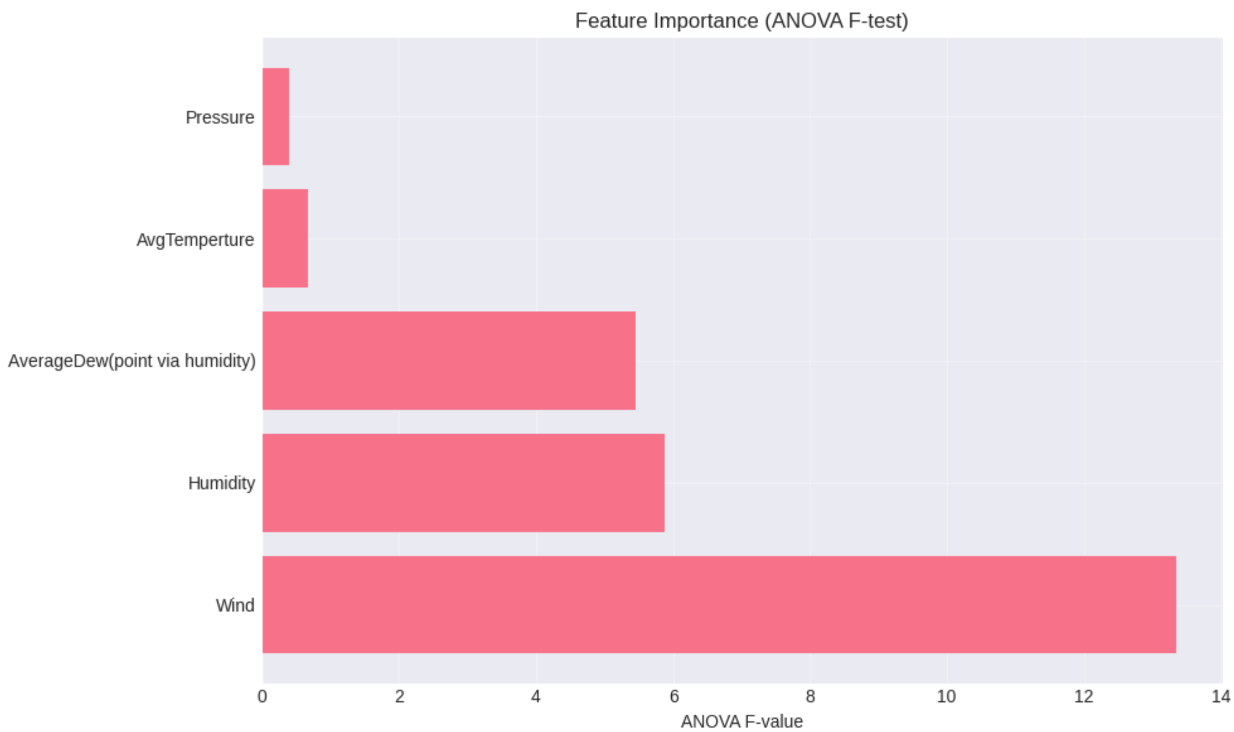
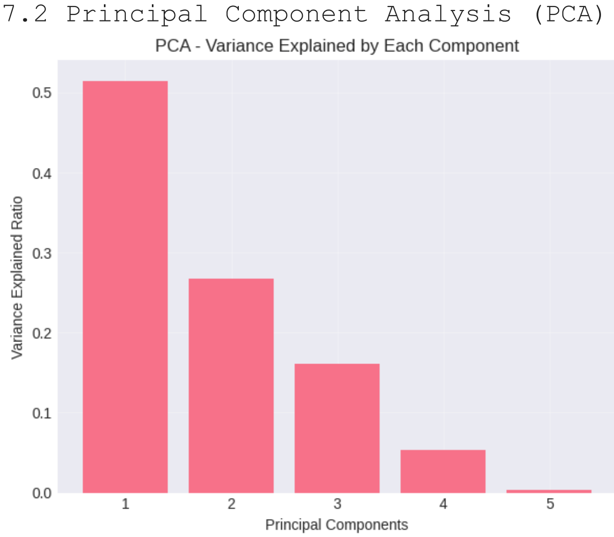
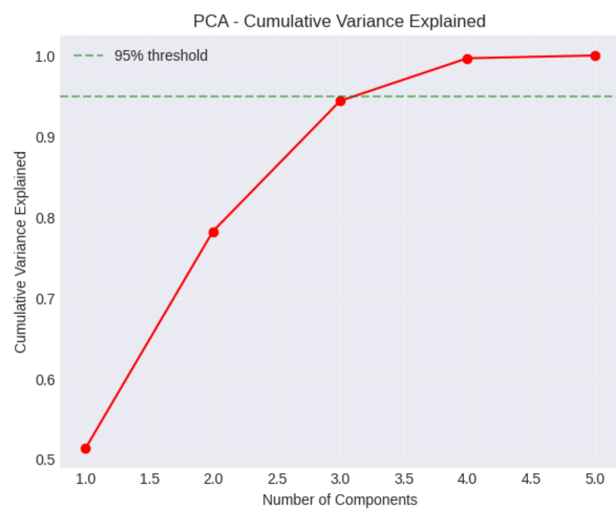
7. FEATURE REDUCTION AND SELECTION
============================================================
7.1 Feature Importance using ANOVA F-value:

Feature importance scores:
                          Feature  F_Score  P_Value
3                            Wind  13.3548   0.0000
2                        Humidity   5.8767   0.0031
1   AverageDew(point via humidity)   5.4467   0.0046
0                    AvgTemperture   0.6640   0.5154
4                        Pressure   0.3989   0.6714
```



7.2 Principal Component Analysis (PCA):

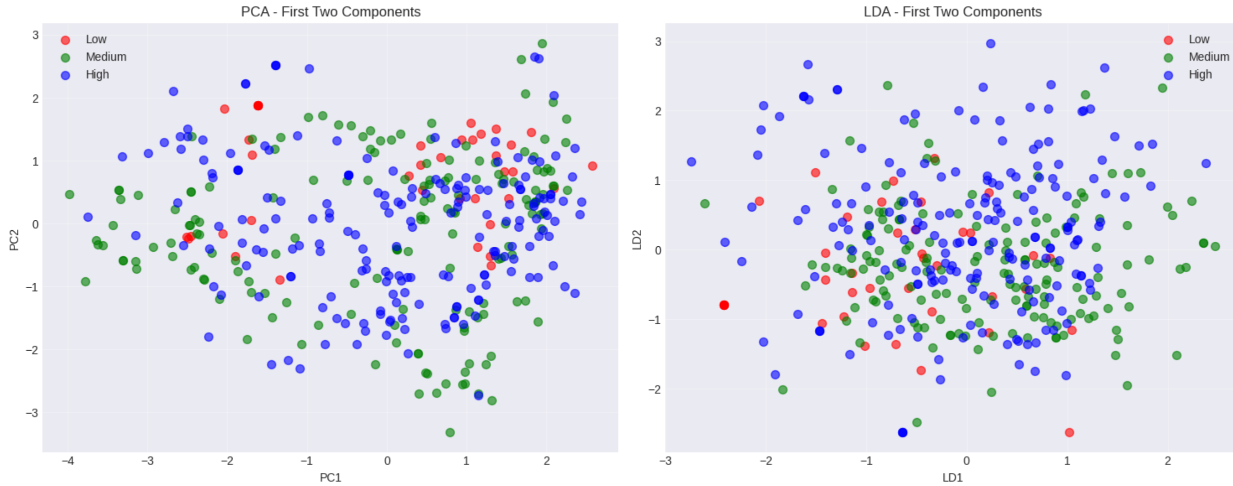





```
Variance explained by each component:
PC1: 51.443%
PC2: 26.805%
PC3: 16.134%
PC4: 5.277%
PC5: 0.342%

Cumulative variance explained:
First 1 components: 51.443%
First 2 components: 78.247%
First 3 components: 94.381%
First 4 components: 99.658%
First 5 components: 100.000%
```

7.3 Linear Discriminant Analysis (LDA):

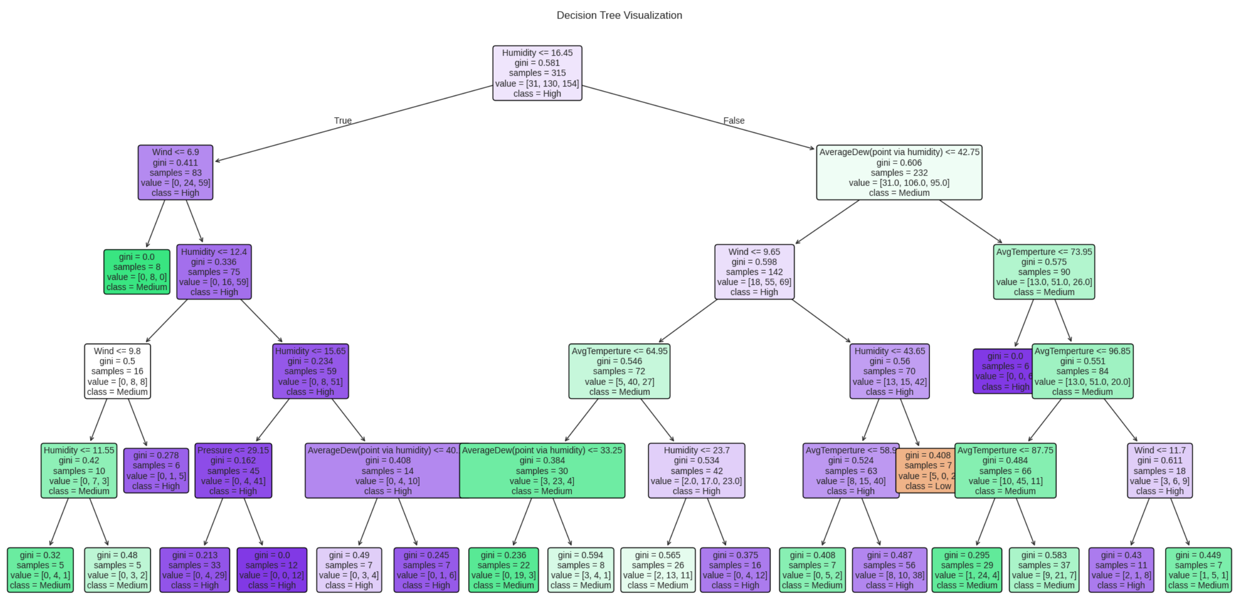



```
============================================================
8. MODEL IMPLEMENTATIONS
============================================================

Value counts for y (coded Solar_Category) before splitting:
2    193
1    162
0     39
Name: count, dtype: int64
Training set size: (315, 5)
Testing set size: (79, 5)
Class distribution in training: [ 31 130 154]
Class distribution in testing: [ 8 32 39]

--------------------------------------------------
8.1 Naive Bayes Classifier:
--------------------------------------------------
Training Accuracy: 0.5238
Testing Accuracy: 0.4684

--------------------------------------------------
8.2 Decision Tree Classifier:
--------------------------------------------------
Training Accuracy: 0.7333
Testing Accuracy: 0.7342
```




```
--------------------------------------------------
8.3 K-Nearest Neighbors with Different Distances:
--------------------------------------------------

K-NN (euclidean):
  Training Accuracy: 0.7270
  Testing Accuracy: 0.6835

K-NN (manhattan):
  Training Accuracy: 0.7175
  Testing Accuracy: 0.7215

K-NN (chebyshev):
  Training Accuracy: 0.7079
  Testing Accuracy: 0.7342

--------------------------------------------------
8.4 LDA Classifier:
--------------------------------------------------
Training Accuracy: 0.5524
Testing Accuracy: 0.5570

--------------------------------------------------
8.5 PCA + Decision Tree Classifier:
--------------------------------------------------
Training Accuracy: 0.7397
Testing Accuracy: 0.6456
Variance explained by 3 PCA components: 99.444%

============================================================
9. MODEL EVALUATIONS
============================================================

Evaluating all models:
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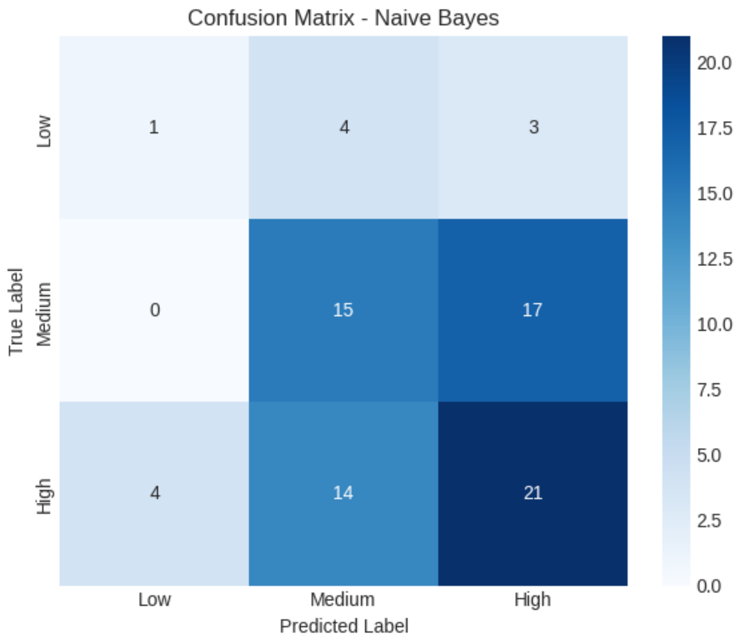
```

```
Naive Bayes Results:
  Training Accuracy: 0.5238
  Testing Accuracy: 0.4684
  Precision: 0.4572
  Recall: 0.4684
  F1-Score: 0.4617
  5-Fold CV Accuracy: 0.5143 (+/- 0.1036)
  Overfitting Gap: 0.0555
```

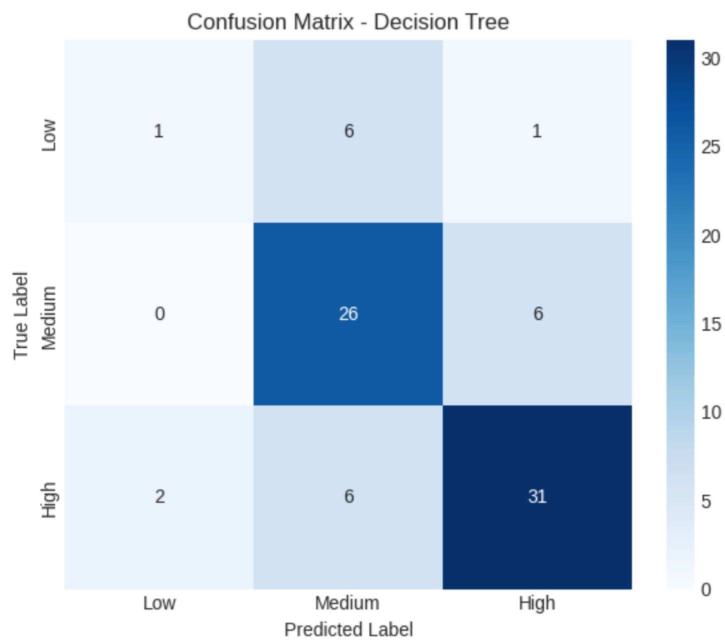



```
  Classification Report:
              precision    recall  f1-score   support

         Low       0.20      0.12      0.15         8
      Medium       0.45      0.47      0.46        32
        High       0.51      0.54      0.53        39

    accuracy                           0.47        79
   macro avg       0.39      0.38      0.38        79
weighted avg       0.46      0.47      0.46        79


Decision Tree Results:
  Training Accuracy: 0.7333
  Testing Accuracy: 0.7342
  Precision: 0.7136
  Recall: 0.7342
  F1-Score: 0.7168
  5-Fold CV Accuracy: 0.5397 (+/- 0.1254)
  Overfitting Gap: -0.0008
```

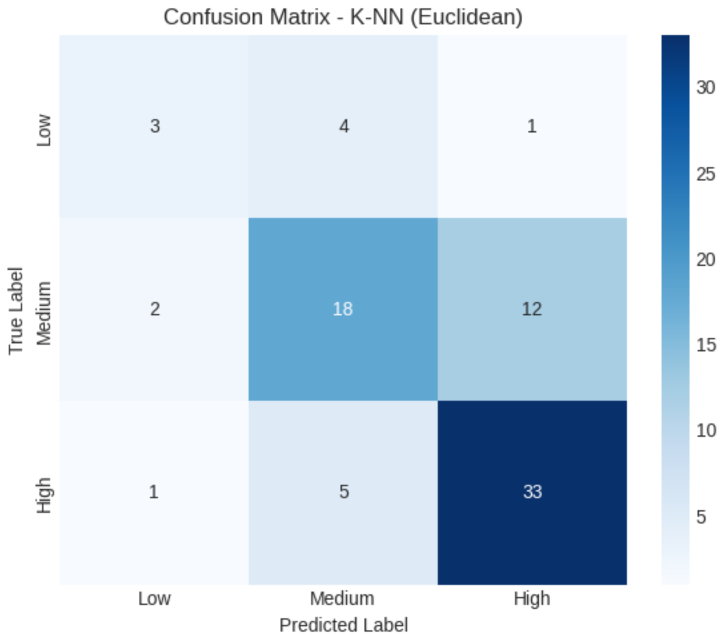



```
  Classification Report:
              precision    recall  f1-score   support

         Low       0.33      0.12      0.18         8
      Medium       0.68      0.81      0.74        32
        High       0.82      0.79      0.81        39

    accuracy                           0.73        79
   macro avg       0.61      0.58      0.58        79
weighted avg       0.71      0.73      0.72        79


K-NN (Euclidean) Results:
  Training Accuracy: 0.7270
  Testing Accuracy: 0.6835
  Precision: 0.6748
  Recall: 0.6835
  F1-Score: 0.6739
  5-Fold CV Accuracy: 0.5810 (+/- 0.1868)
  Overfitting Gap: 0.0434
```

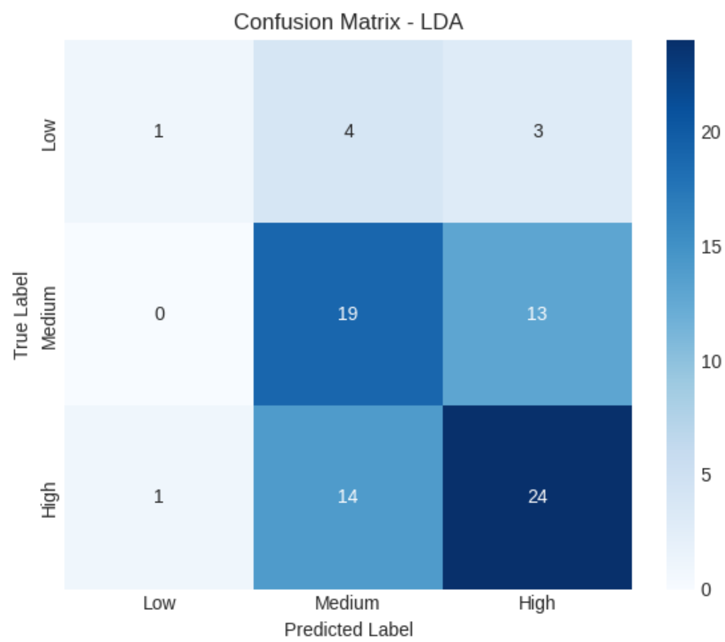



```
  Classification Report:
                precision    recall  f1-score   support

         Low       0.50      0.38      0.43         8
      Medium       0.67      0.56      0.61        32
        High       0.72      0.85      0.78        39

    accuracy                           0.68        79
   macro avg       0.63      0.59      0.61        79
weighted avg       0.67      0.68      0.67        79


LDA Results:
  Training Accuracy: 0.5524
  Testing Accuracy: 0.5570
  Precision: 0.5548
  Recall: 0.5570
  F1-Score: 0.5433
  5-Fold CV Accuracy: 0.5333 (+/- 0.0818)
  Overfitting Gap: -0.0046
```

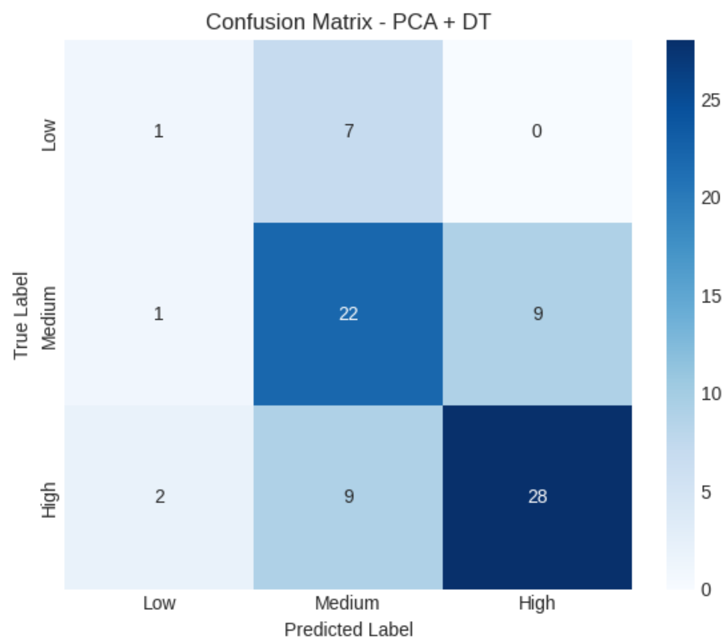



```
  Classification Report:
              precision    recall  f1-score   support

         Low       0.50      0.12      0.20         8
      Medium       0.51      0.59      0.55        32
        High       0.60      0.62      0.61        39

    accuracy                           0.56        79
   macro avg       0.54      0.44      0.45        79
weighted avg       0.55      0.56      0.54        79


PCA + DT Results:
  Training Accuracy: 0.7397
  Testing Accuracy: 0.6456
  Precision: 0.6334
  Recall: 0.6456
  F1-Score: 0.6352
  5-Fold CV Accuracy: 0.5651 (+/- 0.1310)
  Overfitting Gap: 0.0941
```



Classification Report:

	precision	recall	f1-score	support
Low	0.25	0.12	0.17	8
Medium	0.58	0.69	0.63	32
High	0.76	0.72	0.74	39
accuracy			0.65	79
macro avg	0.53	0.51	0.51	79
weighted avg	0.63	0.65	0.64	79

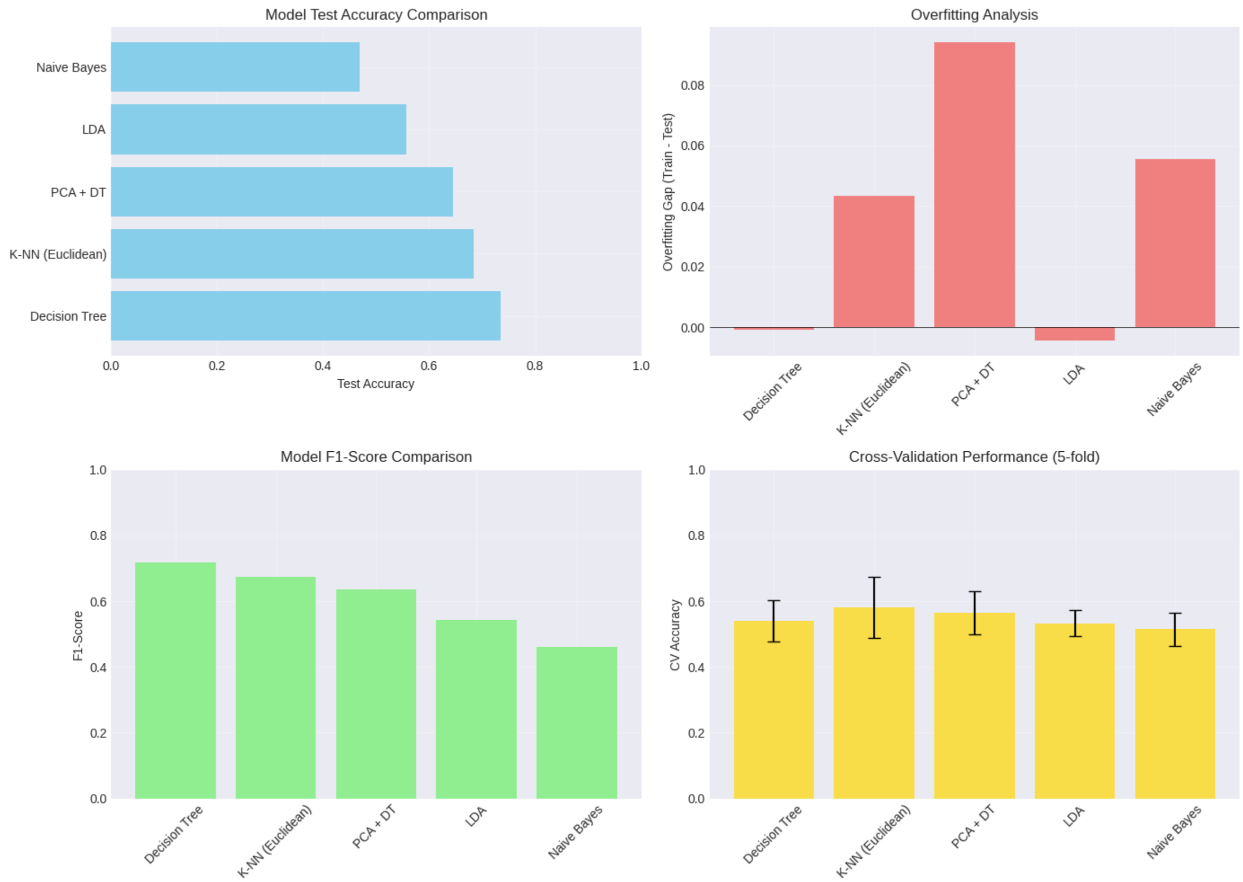
9.1 Model Comparison:

Model Comparison Table:

	Train_Accuracy	Test_Accuracy	Precision	Recall	F1_Score
Decision Tree	0.7333	0.7342	0.7136	0.7342	0.7168
K-NN (Euclidean)	0.7270	0.6835	0.6748	0.6835	0.6739
PCA + DT	0.7397	0.6456	0.6334	0.6456	0.6352
LDA	0.5524	0.5570	0.5548	0.5570	0.5433
Naive Bayes	0.5238	0.4684	0.4572	0.4684	0.4617

\

	CV_Mean	CV_Std	Overfitting_Gap
Decision Tree	0.5397	0.0627	-0.0008
K-NN (Euclidean)	0.5810	0.0934	0.0434
PCA + DT	0.5651	0.0655	0.0941
LDA	0.5333	0.0409	-0.0046
Naive Bayes	0.5143	0.0518	0.0555

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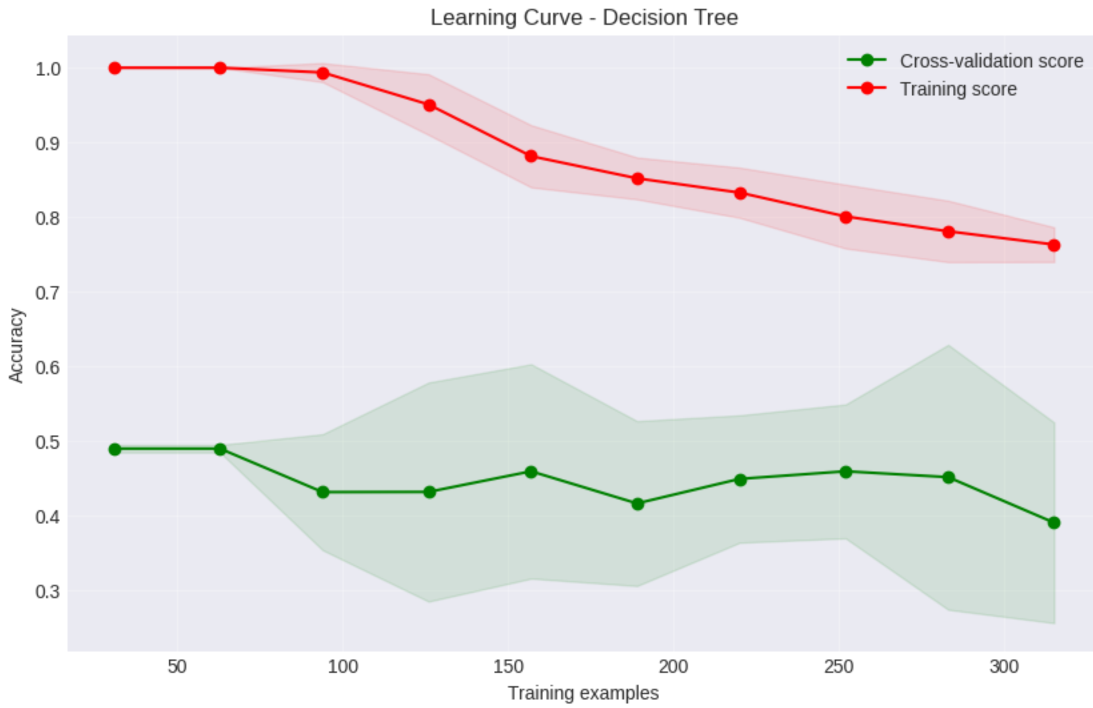
============================================================
10. OVERFITTING/UNDERFITTING ANALYSIS
============================================================

Analyzing Decision Tree for overfitting:
```




```
Overfitting Analysis Summary:
Naive Bayes          | Gap: 0.0555 | Status: Well-fitted
Decision Tree        | Gap: -0.0008 | Status: Well-fitted
K-NN (Euclidean)     | Gap: 0.0434 | Status: Well-fitted
LDA                  | Gap: -0.0046 | Status: Well-fitted
PCA + DT             | Gap: 0.0941 | Status: Well-fitted

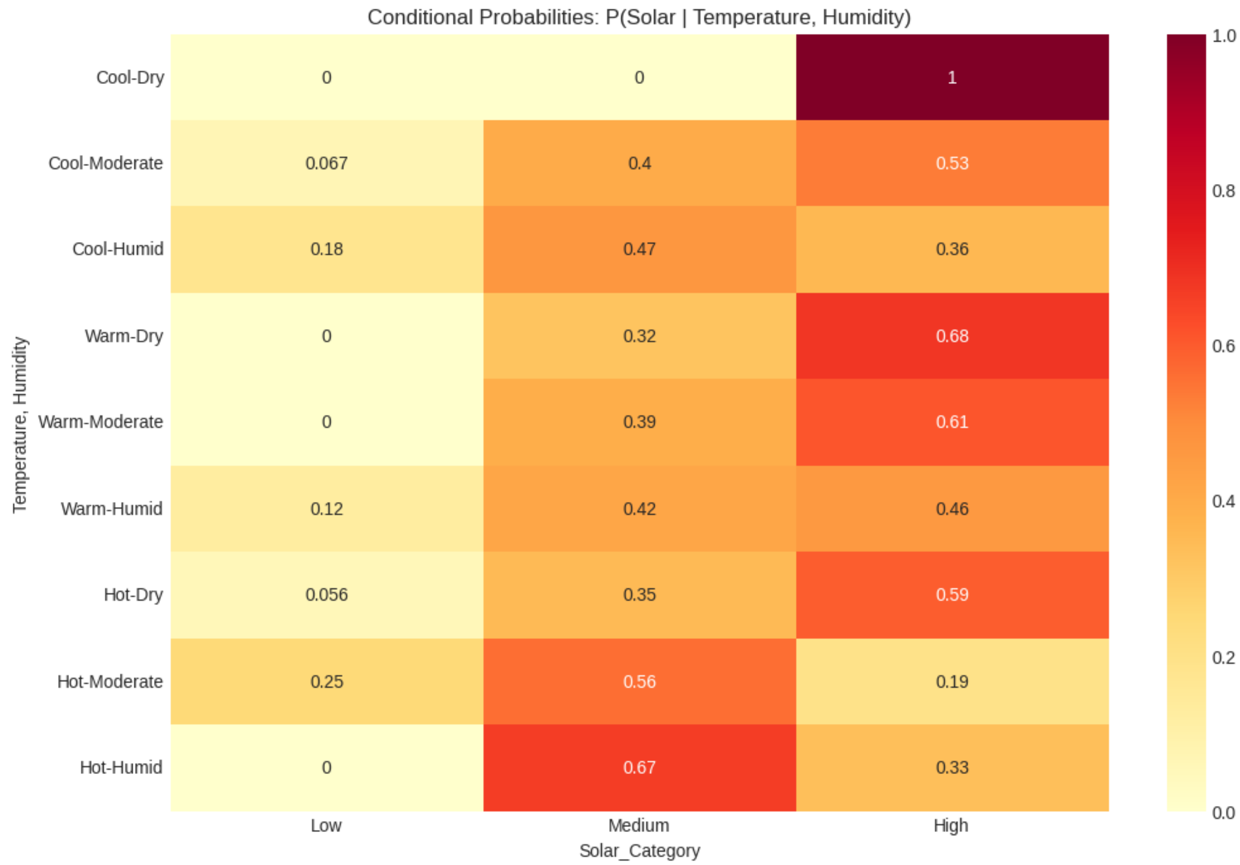
============================================================
11. BAYESIAN BELIEF NETWORK (CONCEPTUAL)
============================================================

Bayesian Belief Network Concept for Solar Prediction:

Structure:
Temperature → Solar Energy ← Humidity
    ↑               ↑           ↑
  Month            Wind       Dew Point
    |
Pressure

Conditional Probability Tables (CPT) would show:
- P(Solar | Temperature, Humidity)
- P(Temperature | Month)
- P(Humidity | Dew Point)
```

```
Empirical Conditional Probabilities:
P(Solar_Category | Temp_Category, Humidity_Category):
------------------------------------------------------------
Solar_Category                      Low  Medium   High
Temp_Category Humidity_Category
Cool          Dry                 0.000   0.000  1.000
              Moderate            0.067   0.400  0.533
              Humid               0.178   0.466  0.356
Warm          Dry                 0.000   0.317  0.683
              Moderate            0.000   0.389  0.611
              Humid               0.125   0.417  0.458
Hot           Dry                 0.056   0.349  0.595
              Moderate            0.246   0.561  0.193
              Humid               0.000   0.667  0.333
```

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8.6 Logistic Regression Classifier:
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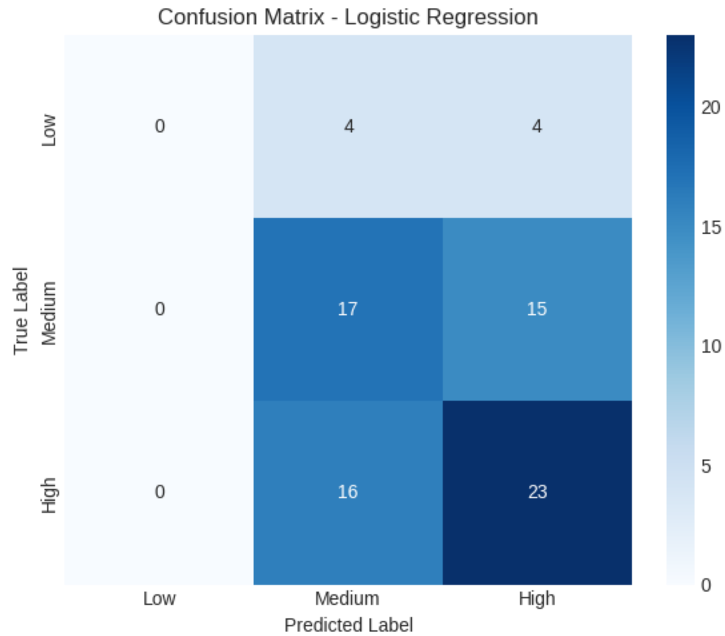
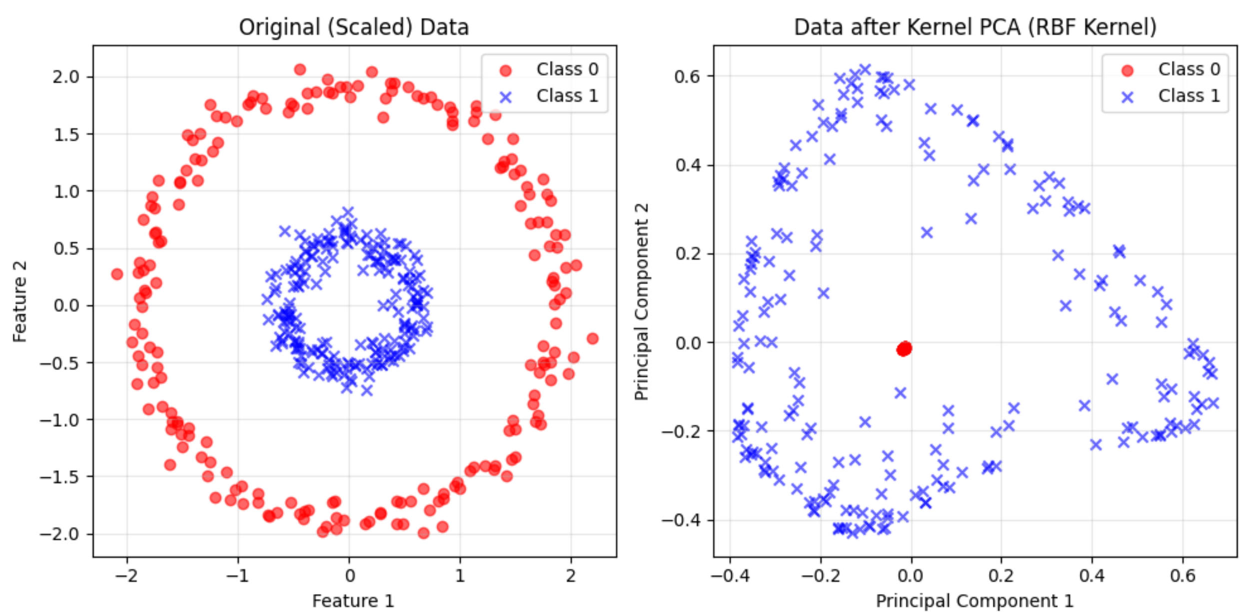
Logistic Regression Results:
  Training Accuracy: 0.5524
  Testing Accuracy: 0.5063
  Precision: 0.4565
  Recall: 0.5063
  F1-Score: 0.4800
  5-Fold CV Accuracy: 0.5429 (+/- 0.0735)
  Overfitting Gap: 0.0461
```



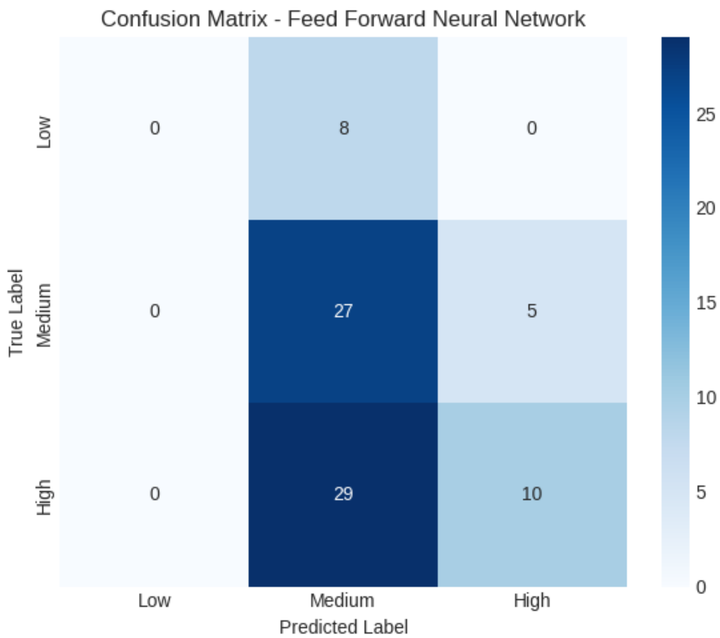
Classification Report:

	precision	recall	f1-score	support
Low	0.00	0.00	0.00	8
Medium	0.46	0.53	0.49	32
High	0.55	0.59	0.57	39
accuracy			0.51	79
macro avg	0.34	0.37	0.35	79
weighted avg	0.46	0.51	0.48	79



8.7 Feed Forward Neural Network:

Feed Forward Neural Network Results:
  Training Accuracy: 0.4984
  Testing Accuracy: 0.4684
  Precision: 0.5000
  Recall: 0.4684
  F1-Score: 0.4107
  5-Fold CV Accuracy: 0.4889 (+/- 0.1353)
  Overfitting Gap: 0.0301

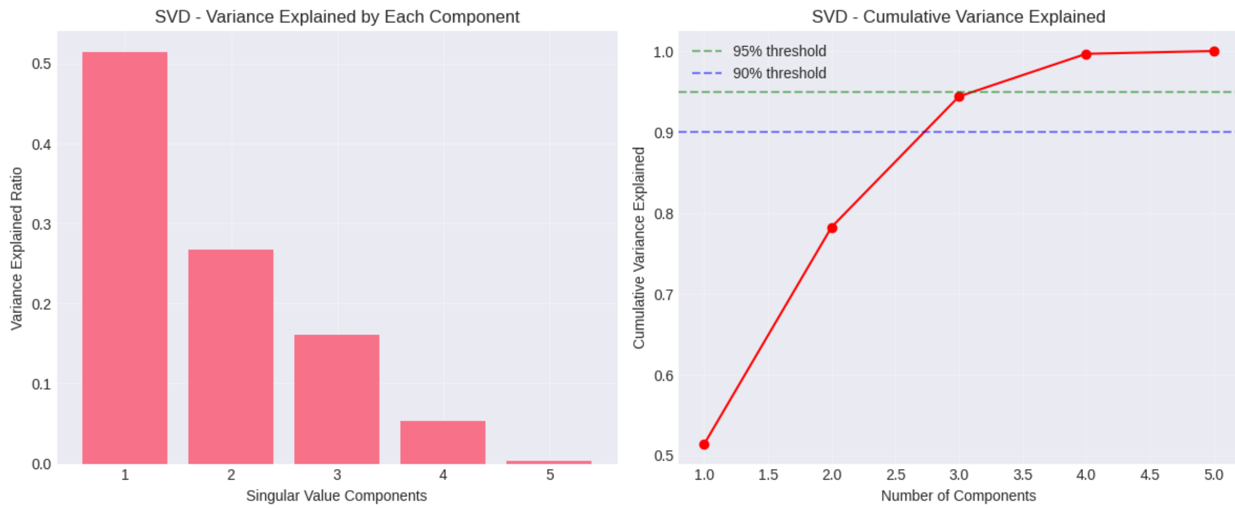


Classification Report:

	precision	recall	f1-score	support
Low	0.00	0.00	0.00	8
Medium	0.42	0.84	0.56	32
High	0.67	0.26	0.37	39
accuracy			0.47	79
macro avg	0.36	0.37	0.31	79
weighted avg	0.50	0.47	0.41	79

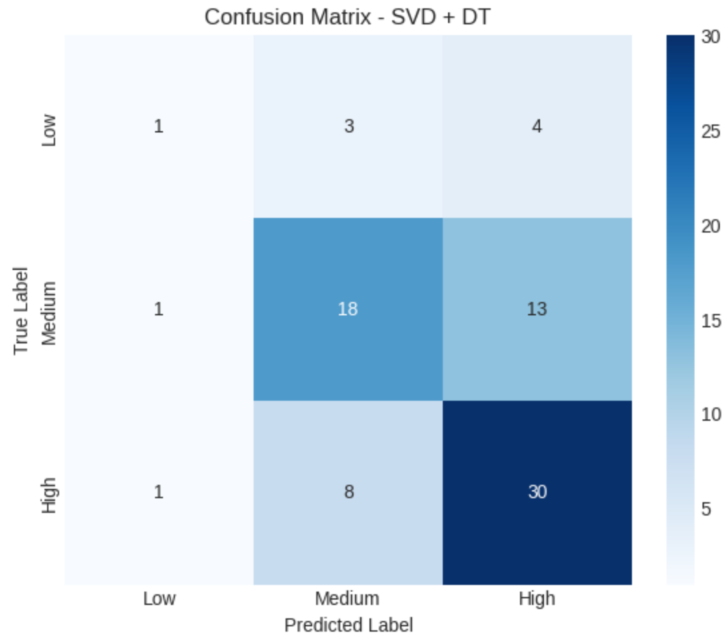
==
8.9 SVD for Dimensionality Reduction and Classification
==
Explained Variance Ratio per component (SVD):
  Component 1: 0.5144
  Component 2: 0.2680
  Component 3: 0.1613
  Component 4: 0.0528
  Component 5: 0.0034

```
Cumulative Explained Variance (SVD):
  Components 1-1: 0.5144
  Components 1-2: 0.7825
  Components 1-3: 0.9438
  Components 1-4: 0.9966
  Components 1-5: 1.0000
```




```
--------------------------------------------------
8.9 SVD + Decision Tree Classifier:
--------------------------------------------------
Original features shape: (394, 5)
SVD-reduced features shape: (394, 3)
Variance explained by 3 SVD components: 94.381%

SVD + DT Results:
  Training Accuracy: 0.6825
  Testing Accuracy: 0.6203
  Precision: 0.6003
  Recall: 0.6203
  F1-Score: 0.6019
  5-Fold CV Accuracy: 0.5460 (+/- 0.1537)
  Overfitting Gap: 0.0623
```



Classification Report:

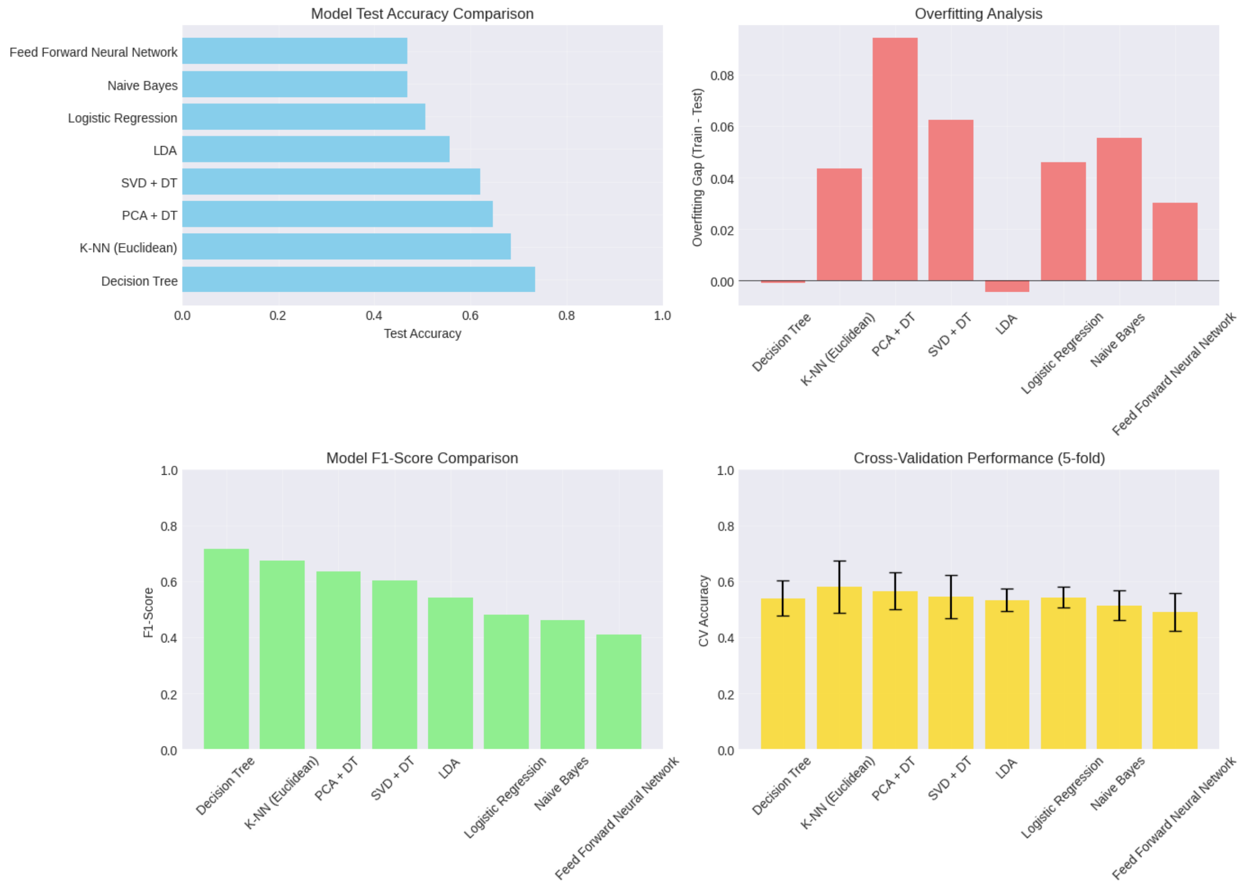
	precision	recall	f1-score	support
Low	0.33	0.12	0.18	8
Medium	0.62	0.56	0.59	32
High	0.64	0.77	0.70	39
accuracy			0.62	79
macro avg	0.53	0.49	0.49	79
weighted avg	0.60	0.62	0.60	79

9.1 Model Comparison (Updated):

Model Comparison Table:

	Train_Accuracy	Test_Accuracy	Precision	Recall
\				
Decision Tree	0.7333	0.7342	0.7136	0.7342
K-NN (Euclidean)	0.7270	0.6835	0.6748	0.6835
PCA + DT	0.7397	0.6456	0.6334	0.6456
SVD + DT	0.6825	0.6203	0.6003	0.6203
LDA	0.5524	0.5570	0.5548	0.5570
Logistic Regression	0.5524	0.5063	0.4565	0.5063
Naive Bayes	0.5238	0.4684	0.4572	0.4684
Feed Forward Neural Network	0.4984	0.4684	0.5000	0.4684

	F1_Score	CV_Mean	CV_Std	Overfitting_Gap
Decision Tree	0.7168	0.5397	0.0627	-0.0008
K-NN (Euclidean)	0.6739	0.5810	0.0934	0.0434
PCA + DT	0.6352	0.5651	0.0655	0.0941
SVD + DT	0.6019	0.5460	0.0768	0.0623
LDA	0.5433	0.5333	0.0409	-0.0046
Logistic Regression	0.4800	0.5429	0.0367	0.0461
Naive Bayes	0.4617	0.5143	0.0518	0.0555
Feed Forward Neural Network	0.4107	0.4889	0.0676	0.0301



Results and Discussion

Dataset Description

The dataset consists of numerical observations collected over time. Multiple features represent observed variables, while the target variable is analyzed as both categorical (classification) and continuous (regression).

Preprocessing Results

- All missing values were eliminated after imputation
- Data visualization revealed seasonal patterns and outliers
- Binning was applied where required for categorical analysis

Descriptive Statistics:

Minimum, maximum, mean, variance, standard deviation, skewness, and kurtosis showed non-normal distributions and high variance in several features.

Statistical Analysis:

- Covariance and correlation matrices revealed strong dependencies
- Heatmaps visualized positive and negative correlations
- Chi-square test confirmed dependence between categorical variables
- t-test and ANOVA showed statistically significant differences across groups

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Feature Reduction Results

- **PCA:** Preserved most variance but reduced classification accuracy
- **LDA:** Achieved better class separation and stable performance
- **SVD:** Reduced dimensionality with moderate effectiveness

Conclusion: LDA outperformed PCA and SVD for classification tasks.

Classification and Regression Results

The dataset was split into **80% training and 20% testing**, and **K-fold cross-validation** was applied.

Table 2: Model Comparison Results

Model	Train Acc	Test Acc	Precision	Recall	F1	CV Mean	CV Std	Overfitting Gap
Decision Tree	0.7333	**0.7342**	0.7136	0.7342	**0.7168**	0.5397	0.0627	-0.0008
K-NN (Euclidean)	0.7270	0.6835	0.6748	0.6835	0.6739	**0.5810**	0.0934	0.0434
PCA + DT	0.7397	0.6456	0.6334	0.6456	0.6352	0.5651	0.0655	0.0941
SVD + DT	0.6825	0.6203	0.6003	0.6203	0.6019	0.5460	0.0768	0.0623
LDA	0.5524	0.5570	0.5548	0.5570	0.5433	0.5333	0.0409	-0.0046
Logistic Regression	0.5524	0.5063	0.4565	0.5063	0.4800	0.5429	0.0367	0.0461
Naive Bayes	0.5238	0.4684	0.4572	0.4684	0.4617	0.5143	0.0518	0.0555
Neural Network	0.4984	0.4684	0.5000	0.4684	0.4107	0.4889	0.0676	0.0301

Interpretation:

- Decision Tree achieved the best performance with minimal overfitting
- K-NN performed well but showed higher variance
- PCA and SVD reduced performance despite variance preservation
- LDA was stable but limited
- Logistic Regression, Naive Bayes, and Neural Network underperformed
- Linear Regression achieved low R^2, indicating poor linear fit

Conclusion and Future Work

This project demonstrated that preprocessing, feature selection, and model choice significantly influence machine learning performance. Decision Tree achieved the highest accuracy (**73.42%**) and F1-score (**0.7168**) with strong generalization. Dimensionality reduction methods did not improve performance, while linear models were unsuitable due to non-linear data relationships.

Future work includes applying ensemble models such as Random Forest and Gradient Boosting, deep learning architectures for temporal modeling, advanced imbalance handling techniques, and larger or more diverse datasets to improve performance and generalization.

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