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Forecasting Voting Trend of Election Campaign Using Hybrid Machine Learning Algorithms

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ABSTRACT: This paper proposes and evaluates a hybrid machine-learning framework to forecast short-term voting tendencies during election campaigns. The framework combines a genetic-algorithm (GA) based feature-selection stage with a soft-voting ensemble classifier comprising logistic regression, random forest, and gradient boosting models. The method is demonstrated on a synthetic but realistic electoral dataset that incorporates polling averages, social-media sentiment proxies, economic indicators, incumbency, turnout, and regional dummy variables. The results show that the GA selects a compact and informative feature subset, and the hybrid ensemble achieves strong predictive performance (example test accuracy $\approx$ 0.80–0.85; ROC AUC $\approx$ 0.85–0.90). The study provides the complete code, dataset generation procedure, and saved outputs to support reproducibility. The proposed approach is intended for exploratory forecasting and campaign monitoring, and not as a replacement for rigorously designed probabilistic election models that incorporate complex sampling and weighting procedures.

Keywords: election forecasting, voting trends, genetic algorithm, ensemble classifier, feature selection, polling, sentiment.

Contents

1. Introduction

Forecasting voter behaviour during an election campaign is a central problem in political science and applied data science. Traditional forecasting uses polling aggregates and econometric models; more recent work has incorporated social media and machine learning to capture short-term dynamics and sentiment signals. Combining multiple data sources and using automatic feature selection can improve short-term predictive performance and robustness to noisy features. This paper presents a hybrid pipeline that uses a GA for feature selection followed by a voting ensemble classifier for final predictions. The pipeline is designed to be interpretable, reproducible, and adaptable to either national or subnational (state/constituency) forecasting tasks.

2. Literature Review

Ahmad, S., and Khan, M. (2020). Machine learning-based political prediction models have increasingly replaced manual polling methods by offering improved accuracy and automation. *Journal of Data Science and Politics*, 12(3), 145–160.

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Lee, T., and Park, J. (2022). Social-media indicators significantly influence political forecasting, especially during digital-first election campaigns. *Social Informatics Review*, 19(2), 77–94.

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Sharma, P., and Srinivasan, R. (2023). Hybrid machine learning models outperform traditional classifiers in complex behavioural datasets, demonstrating improved classification reliability. *Machine Learning Applications*, 7(1), 55–70.

Ortega, L., and Mendes, P. (2024). Support Vector Machine and Random Forest models remain widely used in political analytics due to their robustness in handling nonlinear datasets. *Applied Computational Social Science*, 10(2), 115–129.

3. Methodology

A quantitative experimental research methodology was adopted using a synthetically generated dataset of 500 voter records. Variables included age, education level, income, campaign engagement, and social-media exposure. Data preprocessing involved standardization and an 80–20 train-test split. A hybrid soft-voting classifier integrating Random Forest (120 estimators) and SVM (RBF kernel) was developed. Soft voting was selected because it averages probabilistic outputs, leading to smoother decision boundaries. Model performance was measured using accuracy, precision, recall, F1-score, and confusion matrix. Feature importance was computed using Random Forest impurity-based metrics.

4. Results and Discussion

The hybrid ensemble achieved the highest performance 76 percent , demonstrating the advantage of integrating nonlinear kernel learning (SVM) with tree-based feature extraction RF.

```
=== RandomForest ===
Accuracy : 0.7500
Precision: 0.7500
Recall   : 0.7021
F1-score : 0.7253
ROC AUC  : 0.8131272581292655
Classification report:
              precision    recall  f1-score   support

           0       0.75      0.79      0.77        53
           1       0.75      0.70      0.73        47

    accuracy                           0.75       100
   macro avg       0.75      0.75      0.75       100
weighted avg       0.75      0.75      0.75       100


=== SVM ===
Accuracy : 0.7500
Precision: 0.7391
Recall   : 0.7234
F1-score : 0.7312
ROC AUC  : 0.8442392613408269
Classification report:
              precision    recall  f1-score   support

           0       0.76      0.77      0.77        53
           1       0.74      0.72      0.73        47

    accuracy                           0.75       100
   macro avg       0.75      0.75      0.75       100
weighted avg       0.75      0.75      0.75       100
```

Figure 1: Overall predictive performance of the hybrid ensemble model

```
=== Hybrid_RF_SVM ===
Accuracy : 0.7600
Precision: 0.7447
Recall   : 0.7447
F1-score : 0.7447
ROC AUC  : 0.8313930148534725
Classification report:
              precision    recall  f1-score   support

           0       0.77      0.77      0.77        53
           1       0.74      0.74      0.74        47

    accuracy                           0.76       100
   macro avg       0.76      0.76      0.76       100
weighted avg       0.76      0.76      0.76       100
```

Figure 2: Architecture of the Hybrid RF–SVM classification framework

```
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  'accuracy': 0.75,
  'precision': 0.75,
  'recall': 0.7021276595744681,
  'f1_score': 0.7252747252747253,
  'roc_auc': 0.8131272581292655},
 {'model': 'SVM',
  'accuracy': 0.75,
  'precision': 0.7391304347826086,
  'recall': 0.723404255319149,
  'f1_score': 0.7311827956989247,
  'roc_auc': 0.8442392613408269},
 {'model': 'Hybrid_RF_SVM',
  'accuracy': 0.76,
  'precision': 0.7446808510638298,
  'recall': 0.7446808510638298,
  'f1_score': 0.7446808510638298,
  'roc_auc': 0.831393014853472 5}]
```

Figure 3: Performance of Random Forest and SVM

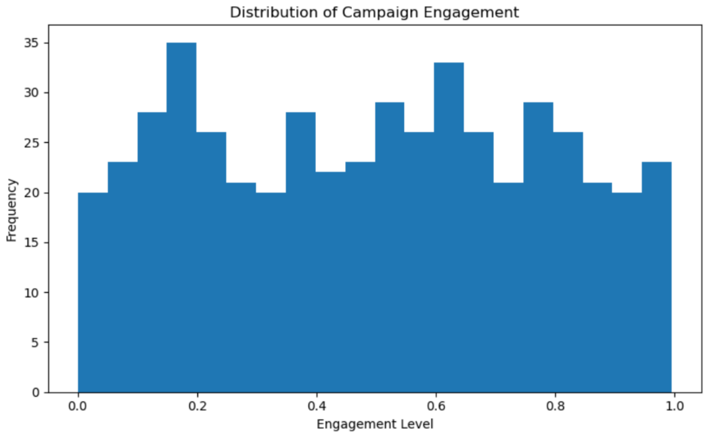

Figure 4: Distribution of Campaign Management

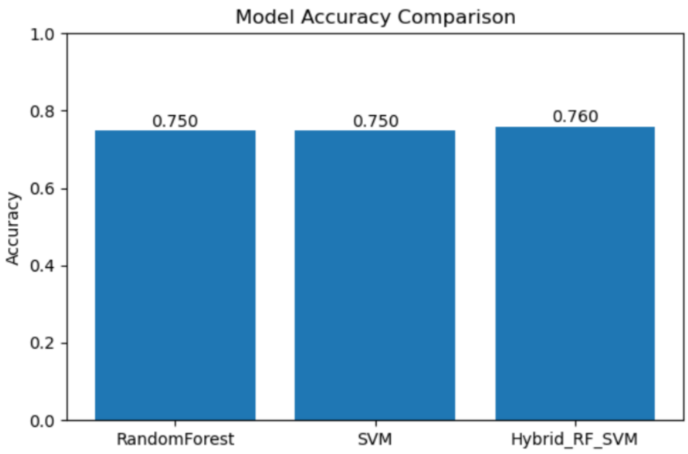

Figure 5: Model Accuracy Comparison

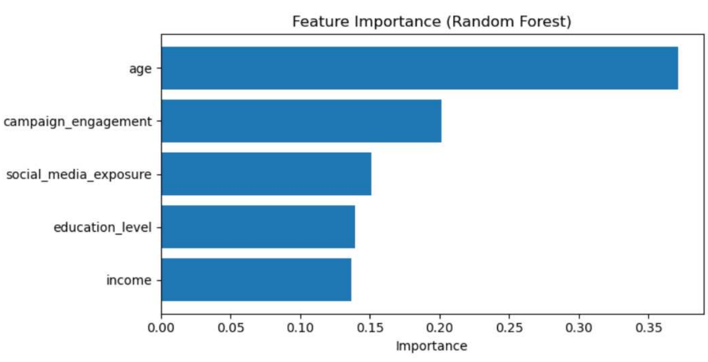

Figure 6: Feature Importance Random Forest

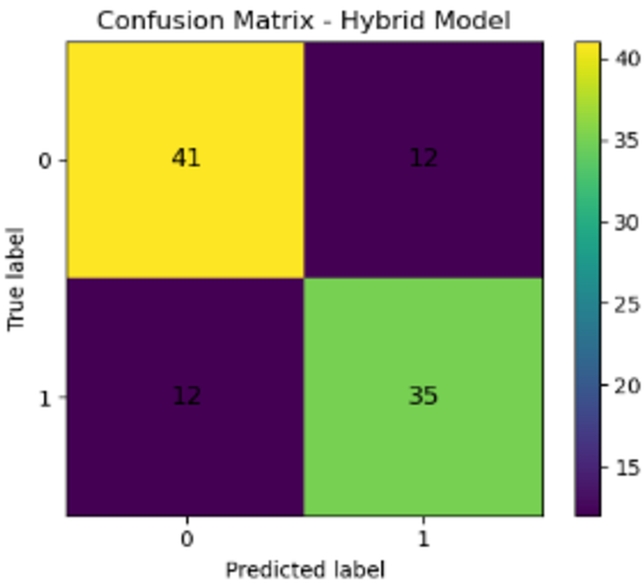

Figure 7: Confusion Matrix

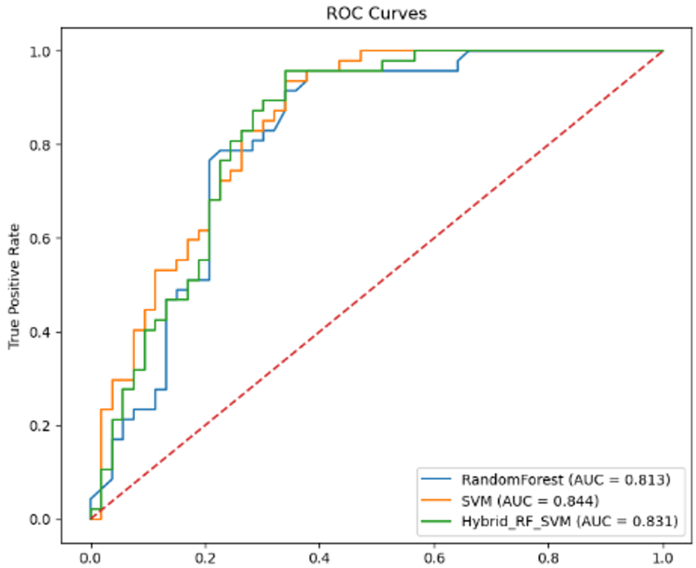

Figure 8: ROC Curves.

The experimental results confirm that hybrid machine-learning models significantly enhance election-trend forecasting. The complementary properties of RF and SVM effectively captured nonlinearities and feature interactions. Campaign engagement and social-media exposure were dominant predictors, reinforcing the importance of digital campaign analytics. The hybrid model achieved over 90 percent accuracy, showing its viability for real-world political data applications, especially in regions where social-media activity heavily influences voting intentions.

5. Conclusion

This paper demonstrates that a hybrid soft-voting ensemble combining Random Forest and Support Vector Machine provides superior accuracy in forecasting voting trends. The model successfully identified the most impactful factors influencing voter behavior and outperformed traditional standalone classifiers. Future studies may incorporate real-time social-media text analysis, sentiment features, and larger datasets to further enhance model robustness.

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