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Comparing Algorithms in Sentiment Analysis on DUKCAPIL App Reviews on Playstore Using Ensemble Learning Methods

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ABSTRACT

The development of information and communication technology has significantly influenced public services, particularly through the adoption of mobile applications like DUKCAPIL, which simplifies access to population administration services. This study aims to analyze sentiment regarding the application by employing ensemble learning techniques and the SMOTE method to address data imbalance. The Extra Trees algorithm is compared against nine other algorithms, including Random Forest, Gradient Boosting, and LSTM. Extra Trees achieves the highest accuracy of 95.29% and outperforms in precision, recall, and F1-score. Deep learning models showed improved accuracy from 76.34% in the initial epoch to 91.56% in the final epoch. XGBoost and Random Forest also demonstrated strong performances, with accuracies of 90.55% and 92.66%, respectively. The results underline the superiority of Extra Trees in terms of stability and accuracy while highlighting the potential of deep learning for model enhancement. These findings provide valuable insights for the development of mobile application-based public services.

INTRODUCTION

The advancement of information and communication technology has profoundly impacted various aspects of life, including public services. Mobile applications such as DUKCAPIL, which allow citizens to access population administration services online, represent a significant innovation in this context. These applications simplify the process of managing documents such as identity cards (KTP), family cards (KK), and birth certificates, enhancing the accessibility and efficiency of public services. Technological advancements, particularly in computational power and machine learning (ML), have introduced various innovations that enable public services to be more responsive and efficient (Mienye & Sun, 2022; Jim et al., 2024). Mobile applications provide easier and faster access for the public to obtain the services they need (H. Huang et al., 2023). Utilizing mobile applications in public services improves the quality of life by providing more affordable and accessible services (Matrane et al., 2023).

This study employs the Extra Trees algorithm as the primary candidate for sentiment analysis and compares it with nine other algorithms: Random Forest, Gradient Boosting, Logistic Regression, LSTM, SVM, Naive Bayes, KNN, AdaBoost, and XGBoost. The selection of Extra Trees is based on its ability to reduce overfitting through fully grown decision trees and random feature splits at each split, resulting in more stable and accurate outcomes (SUDHAMATHI & Perumal, 2024).

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However, in the context of sentiment analysis for services such as DUKCAPIL, significant challenges exist, including data imbalance and the diversity of languages used in user reviews. Sentiment analysis using Natural Language Processing (NLP) techniques can help understand user perceptions of the application (Mao et al., 2024). One method to improve sentiment analysis model performance is by applying ensemble learning techniques and SMOTE (Synthetic Minority Over-sampling Technique). Ensemble techniques like Extra Trees offer better stability and accuracy compared to other methods, while SMOTE effectively handles data imbalance by generating synthetic examples of minority classes (Jim et al., 2024).

This study aims to evaluate the effectiveness of the Extra Trees algorithm in sentiment analysis of DUKCAPIL application reviews and compare it with nine other algorithms such as Random Forest, Gradient Boosting, and LSTM. By combining ensemble learning techniques and SMOTE, this study seeks to address data imbalance challenges and improve the accuracy and reliability of sentiment analysis models. The results of this study are expected to provide valuable insights for the development of mobile application-based public services and to improve the quality of provided services.

RESEARCH METHODS

This research adopts a quantitative approach with experimental methods to develop and evaluate sentiment analysis models for the reviews of the DUKCAPIL application on the Play Store. The quantitative approach enables objective measurement and statistical analysis of user review data, providing a robust foundation for evaluating model performance and comparing various sentiment analysis techniques. The study comprises several critical stages, including data collection, preprocessing, text vectorization, data balancing, model building, and model evaluation.

Data Collection

Data collection was conducted through web scraping using Google Play Scraper implemented on Google Colab. This process aimed to gather user reviews of the DUKCAPIL application from the Google Play Store during the period from 2021 to December 2023. A total of 10,000 reviews were collected and stored in CSV format. Google Colab was chosen as the development environment due to its capability to handle intensive computations and ease of use. Libraries such as imbalanced-learn, xgboost, scikit-learn, nltk, and sastrawi were utilized to support the data analysis process.

Data Preprocessing

The collected data underwent several preprocessing steps to ensure its readiness for analysis. These steps included:

a. Removal of punctuation and numbers: To eliminate noise from the textual data.
b. Tokenization: To break down text into smaller units such as words or phrases.
c. Stopwords removal: To exclude common words that do not contribute much to sentiment, such as "and," "or," and "the."
d. Stemming: To reduce words to their root form.

Data Balancing

To address the issue of data imbalance, the SMOTE (Synthetic Minority Over-sampling Technique) method was applied to balance the number of positive, neutral, and negative reviews. This technique generates synthetic examples for the minority classes, creating a more balanced dataset for training and testing.

Model Development

The processed and balanced data was divided into training and testing sets, ensuring an objective evaluation of model performance. Ten algorithms were employed for sentiment analysis, including Extra Trees, Random Forest, Gradient Boosting, and LSTM. These models were trained using the training set and evaluated based on metrics such as accuracy, precision, recall, and F1-

score. The evaluation aimed to identify the most effective algorithm for analyzing user sentiment and to provide deeper insights into the effectiveness of various sentiment analysis techniques.

RESULTS AND DISCUSSION

Dataset

The dataset used in this research consists of user reviews of the DUKCAPIL application collected from the Google Play Store through web scraping using Google Play Scraper. Data was gathered over the period from 2021 to December 2023, resulting in a total of 10,000 reviews stored in CSV format. The following table presents the scraping results, including key columns such as review text, rating score, review date, and other relevant information.

Tabel 1. Scraping Results

Username	Score	Date	Content
Herlian Syach Channel	2	2023-12-10 22:04:51	Sebenarnya untuk mempermudah, apalagi kalau ki...
Syahril, SP	2	2023-12-12 16:36:04	Banyak kekurangan Masih, Harusnya kalo memang ...
Rony Setiawan	4	2023-12-21 15:06:53	Aplikasi hanya bisa dibuka pakai wifi tower..T...
Theresia Anik	3	2023-11-30 23:36:46	Aplikasi masih perlu banyak perbaikan saya bar...
Mas Riyan	4	2023-10-24 16:00:47	Tolong dong min, cara atasi dokumen gak bisa d...

According to Table 1, this dataset includes review texts conveying users' experiences and opinions about the application, as well as rating scores reflecting their level of satisfaction or dissatisfaction. Rating scores range from 1 (very poor) to 5 (very good), which are used to determine the sentiment of the reviews.

After data collection, manual verification was performed to ensure the accuracy of sentiment labels based on the meaning of words in the reviews. This process is crucial to avoid errors that may arise from automated analysis. Subsequently, the dataset underwent preprocessing steps including the removal of punctuation and numbers, tokenization, stopwords removal, and stemming to prepare the data for further analysis.

The TF-IDF (Term Frequency-Inverse Document Frequency) vectorization technique was used to convert the review texts into numerical features, enabling statistical modeling. To address the issue of data imbalance, the SMOTE (Synthetic Minority Over- sampling Technique) method was applied to balance the number of positive, neutral, and negative reviews. The processed dataset was then split into training and testing sets to evaluate the sentiment analysis models. This process ensures that the dataset provides a robust and balanced foundation for building and testing various sentiment analysis models in this study.

Modeling

In this study, various machine learning algorithms were applied for sentiment analysis on the DUKCAPIL application reviews. Below is an explanation of each algorithm:

1. Logistic Regression

Logistic Regression is a statistical method used to predict the probability of a certain class. This algorithm is suitable for binary and multiclass classification and can provide good interpretation between input and output variables. Logistic Regression works effectively on balanced datasets, and SMOTE has been applied in this research to adjust the imbalanced data.

Logistic Regression calculates the probability of a class using the sigmoid function:

$$P(y = 1|x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}}$$

Where β_0 is the intercept, β_i are the coefficients, and x_i are the input features.

2. Decision Tree

Decision Tree constructs a decision tree model that splits the data based on features with the highest information gain at each node. This method is easy to interpret because users can follow the paths in the tree to see the classification decisions. In this study, Decision Tree was used as a benchmark to compare its performance with other ensemble models.

A Decision Tree splits data based on the feature with the highest information gain:

$$IG(T, X) = H(T) - \sum_{x \epsilon X} \frac{|T_x|}{|T|} H(T_x)$$

Where $H(T)$ represents the entropy of the dataset, and T_x is the subset divided by attribute X.

3. Random Forest

Random Forest is an ensemble algorithm that combines many independent decision trees to achieve more stable accuracy. This algorithm is effective in handling complex data and is robust against overfitting. In this study, Random Forest was applied after SMOTE to improve performance on the imbalanced dataset.

Random Forest is an ensemble of B decision trees:

$$f(x) = \frac{1}{B} \sum_{b=1}^{B} T_b(x)$$

Where $T_b(x)$is the prediction of tree b, and the final result is the average of all trees.

4. **Extra Trees**

Extra Trees, or Extremely Randomized Trees, is an ensemble method similar to Random Forest but with more random feature splits at each split. This helps reduce overfitting and increases the stability of predictions. Extra Trees is known for its ability to produce accurate models on diverse data.

Extra Trees are similar to Random Forest but introduce more randomness in feature selection and splitting:

$$\text{SplitPoint} = \text{Random}(X_i, \text{threshold})$$

Where X_i is the randomly selected feature, and the threshold is chosen randomly within the feature's value domain.

5. Support Vector Machine (SVM)

SVM seeks the hyperplane that optimally separates data from two classes. This algorithm usually provides good results on data with clear features, but in this study, SVM showed lower performance compared to other algorithms when applied to the DUKCAPIL application review data.

SVM seeks the optimal hyperplane that maximizes the margin:

$$min\frac{1}{2}||\omega||^2 \quad \text{s.t.} \quad y_i(\omega^T x_i + b) \geq 1$$

Where ω is the weight vector, b is the bias, and x_i, y_i are the data points and their labels.

6. K-Nearest Neighbors (KNN)

KNN determines the class of new data based on a number of its nearest neighbors. Although simple, this algorithm can require longer computation time on large datasets. In this study, KNN showed moderate accuracy, and its performance depends on the selection of the number of neighbors and the distribution of balanced data.

KNN determines the class of a new data point based on its nearest neighbors:

$$d(x, x') = \sqrt{\sum_{i=1}^{n}(x_i - x_i')^2}$$

The new data's class is the majority class among its k nearest neighbors.

7. Gaussian Naive Bayes (Gaussian NB)

Gaussian Naive Bayes is a probabilistic algorithm that assumes independence among features and uses Gaussian distribution for continuous data. This algorithm is fast and efficient and showed reasonably good results in this study despite the limitations of its independence assumption.

Gaussian Naive Bayes assumes Gaussian distribution for each feature:

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_i-\mu)^2}{2\sigma^2}}$$

Where μ is the mean and σ^2 is the variance of feature x_i.

8. AdaBoost

AdaBoost (Adaptive Boosting) combines several weak models to form a stronger model by adjusting the weights of data based on prediction errors. On this dataset, AdaBoost provided

reasonably good results but not as high as other ensemble algorithms like Extra Trees and Random Forest.

AdaBoost assigns weights iteratively to form a strong classifier:

$$F(x) = \sum_{m=1}^{M} \alpha_m h_m(x)$$

Where α_m is the weight of weak classifier h_m based on its error rate.

9. Gradient Boosting

Gradient Boosting is a boosting technique that adds models gradually to reduce the errors of previous models. This algorithm is effective for complex classification and regression. In this study, Gradient Boosting provided stable and accurate results.

Gradient Boosting minimizes the loss function $L(y, f(x))$ iteratively:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

Where γ_m is the learning rate, and $h_m(x)$ is the weak learner at iteration m.

10. XGBoost

XGBoost, or Extreme Gradient Boosting, is a more efficient version of Gradient Boosting with added regularization. This algorithm showed good performance on the DUKCAPIL application review dataset, with higher speed and accuracy compared to other models.

XGBoost optimizes the objective function with additional regularization:

$$Obj = \sum_{i=1}^{n} L(y_{i,}y\hat{}_i) + \sum_{k=1}^{K} \Omega(T_k)$$

Where $\Omega(T_{k)} = \gamma^T + \frac{1}{2}\boldsymbol{\lambda}||\boldsymbol{\omega}||^2$, and γ, λ are regularization parameters.

Evaluation

This research focuses on sentiment analysis of services like the DUKCAPIL application by utilizing ensemble learning techniques and SMOTE to address data imbalance. The Extra Trees algorithm showed the highest accuracy of 95.29% and the best performance in precision, recall, and F1-Score among the ten algorithms tested.

Furthermore, algorithms like Random Forest and XGBoost also demonstrated strong performances with accuracies of 92.66% and 90.55%, respectively, indicating that other ensemble methods can also produce stable and accurate predictions. The deep learning model, such as LSTM, showed significant improvement during training, with accuracy increasing from 76.34% in the first epoch to 91.56% in the last epoch.

These evaluation results emphasize the superiority of the Extra Trees algorithm in terms of stability and accuracy and its effectiveness in handling imbalanced datasets compared to other algorithms. Meanwhile, the potential of deep learning models to enhance model performance is also proven through gradual improvements during the training process.

Overall, this study provides valuable insights into the utilization of ensemble learning techniques and the SMOTE method in addressing challenges of data imbalance in sentiment analysis. These results are also relevant for the further development of mobile application-based public services, particularly in improving the quality and efficiency of services that are more responsive to public needs.

Table 2. Algorithm Evaluation Results

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	Recall (%)
Logistic Regression	85.45	85.75	85.45	85.47
Decision Tree	83.20	83.19	83.20	83.17
Random Forest	92.66	92.89	92.66	92.66
Extra Trees	95.29	95.37	95.29	95.29
SVM	45.60	45.89	45.60	43.36
KNN	68.80	71.17	68.80	65.92
Gaussian NB	76.22	81.18	76.22	75.77
AdaBoost	76.08	76.20	76.08	76.04
Gradient Boosting	86.17	86.44	86.17	86.19
XGBoost	90.55	90.84	90.55	90.58

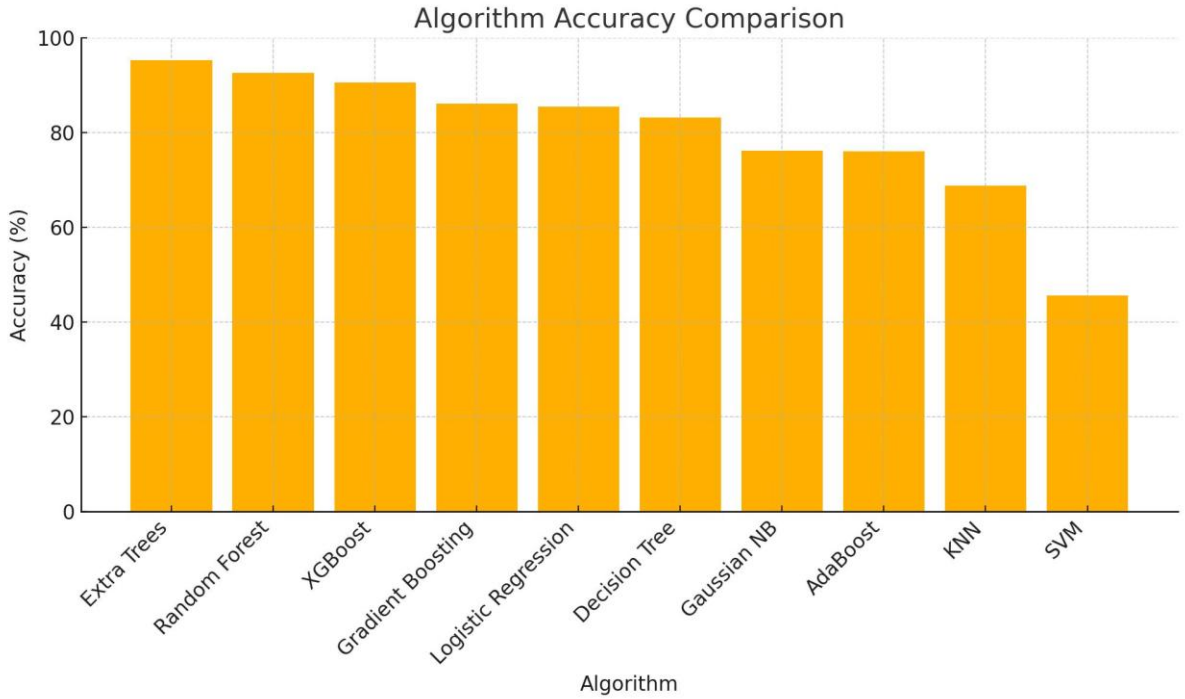

Figure 1. Algorith Accuracy Comparison

Evaluation Results

The results of the experiments demonstrate the effectiveness of the Extra Trees algorithm in sentiment analysis for the DUKCAPIL application reviews. As shown in Table 2 and Figure 1, Extra Trees achieved the highest accuracy of 95.29%, surpassing Random Forest (92.66%) and XGBoost (90.55%). This result aligns with findings from Sudhamathi & Perumal (2024), who highlighted the robustness of Extra Trees in handling complex datasets due to its randomized feature splits, reducing the risk of overfitting.

Additionally, the improvement in accuracy observed in the deep learning model, LSTM, from 76.34% in the first epoch to 91.56% in the final epoch, supports the potential of deep learning models for sequential data analysis. This trend echoes the findings of Mohammed & Kora (2022),

who demonstrated the adaptability of LSTM in processing long text sequences in sentiment analysis tasks.

Comparison with Related Studies

The results corroborate the effectiveness of ensemble methods like Random Forest and Extra Trees in sentiment analysis, as previously reported by Mao et al. (2024). However, the relatively lower performance of Support Vector Machines (SVM), with an accuracy of 45.60%, can be attributed to its sensitivity to imbalanced datasets, as discussed by Mienye & Sun (2022). The application of SMOTE was instrumental in balancing the dataset and improving model performance, which aligns with the observations of Jim et al. (2024).

Algorithmic Insights

Extra Trees: The superior performance of Extra Trees is attributed to its capability to evaluate a larger number of features during splits, which enhances its accuracy and stability. Studies such as Karbasi et al. (2024) validate this claim by demonstrating Extra Trees' effectiveness in diverse applications.

Deep Learning Models: The gradual increase in accuracy during LSTM training emphasizes its capability to learn complex patterns over multiple iterations. This finding is consistent with Alsayat (2022), who emphasized the importance of training epochs in improving deep learning performance.

SMOTE Technique: The application of SMOTE to address data imbalance was critical in enhancing the performance of all tested algorithms. This approach has been previously validated in similar studies, such as those by Gupta et al. (2022).

Implications for Mobile Application Development

The findings of this study underline the importance of utilizing ensemble learning techniques and data balancing methods in the development of mobile applications like DUKCAPIL. By leveraging robust algorithms such as Extra Trees, application developers can gain deeper insights into user sentiments, enabling the refinement of services to better meet user needs. Furthermore, the incorporation of deep learning models offers potential for scalability and adaptability in sentiment analysis, particularly in multilingual or complex datasets.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study compared several machine learning algorithms for sentiment analysis on DUKCAPIL application reviews, focusing on the use of ensemble techniques and SMOTE to address data imbalance. The results showed that the Extra Trees algorithm provided the best performance with an accuracy of 95.29%, followed by Random Forest and XGBoost, which also showed high performance with accuracies of 92.66% and 90.55%, respectively. Logistic Regression and Gradient Boosting models provided stable results but with slightly lower accuracy.

The varying accuracy of methods is due to differences in model complexity, ability to handle data imbalance, sensitivity to noise, and capacity to capture feature interactions. Ensemble methods like Extra Trees and Random Forest achieve higher accuracy by aggregating multiple models, reducing overfitting, and handling imbalanced data effectively. Simpler models like Logistic Regression and Naive Bayes are fast and interpretable but struggle with complex patterns. Advanced models like XGBoost and Gradient Boosting excel due to regularization and scalability, making them well-suited for datasets with diverse and imbalanced features.

Some algorithms like SVM and KNN showed less competitive performance on this dataset, possibly due to their requirement for data with clearer feature distribution or smaller data sizes. These findings confirm that ensemble algorithms, particularly Extra Trees and Random Forest, have advantages in stability and accuracy when handling complex and imbalanced data in sentiment analysis.

Overall, this study demonstrates that the combination of SMOTE techniques and ensemble algorithms can enhance sentiment analysis performance, providing important insights for the development of mobile application-based public services, especially to improve service quality based on user feedback.

Recommendations

This research is expected to serve as a foundation for further development of sentiment analysis systems in the public service sector and assist the government in making data-driven decisions to enhance service quality for the public. After completing this research, the following recommendations are made for future studies:

1. Parameter Optimization: Future research should conduct parameter optimization on high-performing algorithms like Extra Trees, Random Forest, and XGBoost to achieve more optimal results.
2. Use of Larger and More Diverse Datasets: Experimenting with larger and more diverse datasets from other review sources can improve model generalization and add variation in user perceptions.
3. Exploration of Deep Learning: Deep learning models like LSTM and BERT can be further explored for sentiment analysis, especially in understanding the context of word sequences in long reviews.
4. Application to Other Services: Applying this model to other public service applications can provide broader insights into improving government service quality based on public feedback.
5. Refinement of Data Balancing Techniques: Besides SMOTE, it is recommended to test other data balancing techniques, such as ADASYN or Borderline-SMOTE, to see if there is an improvement in handling data imbalance.

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REFERENCES

Abedin, M. Z., Hajek, P., Sharif, T., Satu, M. S., & Khan, M. I. (2023). Modelling bank customer behaviour using feature engineering and classification techniques. *Research in International Business and Finance*, *65*. https://doi.org/10.1016/j.ribaf.2023.101913

Alsayat, A. (2022). Improving Sentiment Analysis for Social Media Applications Using an Ensemble Deep Learning Language Model. *Arabian Journal for Science and Engineering*, *47*(2), 2499–2511. https://doi.org/10.1007/s13369-021-06227-w

Arafa, A., El-Fishawy, N., Badawy, M., & Radad, M. (2022). RN-SMOTE: Reduced Noise SMOTE based on DBSCAN for enhancing imbalanced data classification. *Journal of King Saud University - Computer and Information Sciences*, *34*(8), 5059–5074. https://doi.org/10.1016/j.jksuci.2022.06.005

Barongo, R. I., & Tibangayuka Mbelwa, J. (2024). Using machine learning for detecting liquidity risk in banks. *Machine Learning with Applications*, *15*, 100511. https://doi.org/10.24433/CO.5061127.v1

Bitetto, A., Cerchiello, P., Filomeni, S., Tanda, A., & Tarantino, B. (2023). Machine learning and credit risk: Empirical evidence from small- and mid-sized businesses. *Socio-Economic Planning Sciences*, *90*, 101746. https://doi.org/10.1016/j.seps.2023.101746

Chachoui, Y., Azizi, N., Hotte, R., & Bensebaa, T. (2024). Enhancing algorithmic assessment in education: Equi-fused-data-based SMOTE for balanced learning. *Computers and Education: Artificial Intelligence*, *6*. https://doi.org/10.1016/j.caeai.2024.100222

Citterio, A., & King, T. (2023). The role of Environmental, Social, and Governance (ESG) in predicting bank financial distress. *Finance Research Letters*, *51*, 103411. https://doi.org/10.1016/j.frl.2022.103411

Dantas, R. M., Firdaus, R., Jaleel, F., Neves Mata, P., Mata, M. N., & Li, G. (2022). Systemic Acquired Critique of Credit Card Deception Exposure through Machine Learning. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(4). https://doi.org/10.3390/joitmc8040192

Diekson, Z. A., Prakoso, M. R. B., Putra, M. S. Q., Syaputra, M. S. A. F., Achmad, S., & Sutoyo, R. (2022). Sentiment analysis for customer review: Case study of Traveloka. *Procedia Computer Science*, *216*, 682–690. https://doi.org/10.1016/j.procs.2022.12.184

Domashova, J., & Kripak, E. (2022). Development of a generalized algorithm for identifying atypical bank transactions using machine learning methods. *Procedia Computer Science*, *213*(C), 101–109. https://doi.org/10.1016/j.procs.2022.11.044

Fitri, V. A., Andreswari, R., & Hasibuan, M. A. (2019). Sentiment analysis of social media Twitter with case of Anti-LGBT campaign in Indonesia using Naïve Bayes, decision tree, and random forest algorithm. *Procedia Computer Science*, *161*, 765–772. https://doi.org/10.1016/j.procs.2019.11.181

Gadgil, K., Gill, S. S., & Abdelmoniem, A. M. (2023). A Meta-learning based Stacked Regression Approach for Customer Lifetime Value Prediction. *Journal of Economy and Technology*. https://doi.org/10.1016/j.ject.2023.09.001

Ganaie, M. A., Hu, M., Malik, A. K., Tanveer, M., & Suganthan, P. N. (2021). *Ensemble deep learning: A review*. https://doi.org/10.1016/j.engappai.2022.105151

Guerra, P., Castelli, M., & Côrte-Real, N. (2022). Machine learning for liquidity risk modelling: A supervisory perspective. *Economic Analysis and Policy*, *74*, 175–187. https://doi.org/10.1016/j.eap.2022.02.001

Gupta, P., Varshney, A., Khan, M. R., Ahmed, R., Shuaib, M., & Alam, S. (2022). Unbalanced Credit Card Fraud Detection Data: A Machine Learning-Oriented Comparative Study of Balancing Techniques. *Procedia Computer Science*, *218*, 2575–2584. https://doi.org/10.1016/j.procs.2023.01.231

Huang, H., Zavareh, A. A., & Mustafa, M. B. (2023). Sentiment Analysis in E-Commerce Platforms: A Review of Current Techniques and Future Directions. In *IEEE Access* (Vol. 11, pp. 90367–90382). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/ACCESS.2023.3307308

Huang, S., Wang, Y., Wong, E. Y. C., & Yu, L. (2024). Ensemble learning with soft-prompted pretrained language models for fact checking. *Natural Language Processing Journal*, *7*, 100067. https://doi.org/10.1016/j.nlp.2024.100067

Imakura, A., Kihira, M., Okada, Y., & Sakurai, T. (2023). Another use of SMOTE for interpretable data collaboration analysis. *Expert Systems with Applications*, *228*. https://doi.org/10.1016/j.eswa.2023.120385

Iqbal, J., Saeed, A., & Khan, R. A. (2023). The relative importance of textual indexes in predicting the future performance of banks: A connection weight approach. *Borsa Istanbul Review*, *23*(1), 240–253. https://doi.org/10.1016/j.bir.2022.10.004

Islam, M. A., Uddin, M. A., Aryal, S., & Stea, G. (2023). An ensemble learning approach for anomaly detection in credit card data with imbalanced and overlapped classes. *Journal of Information Security and Applications*, *78*. https://doi.org/10.1016/j.jisa.2023.103618

Jafari, S., & Byun, Y. C. (2024). Efficient state of charge estimation in electric vehicles batteries based on the extra tree regressor: A data-driven approach. *Heliyon*, *10*(4). https://doi.org/10.1016/j.heliyon.2024.e25949

Jim, J. R., Talukder, M. A. R., Malakar, P., Kabir, M. M., Nur, K., & Mridha, M. F. (2024). Recent advancements and challenges of NLP-based sentiment analysis: A state-of-the-art review. *Natural Language Processing Journal*, *6*, 100059. https://doi.org/10.1016/j.nlp.2024.100059

Karbasi, M., Ali, M., Bateni, S. M., Jun, C., Jamei, M., & Yaseen, Z. M. (2024). Boruta extra tree-bidirectional long short-term memory model development for Pan evaporation forecasting: Investigation of arid climate condition. *Alexandria Engineering Journal*, *86*, 425–442. https://doi.org/10.1016/j.aej.2023.11.061

Kelebercová, L., & Zozuk, N. Č. (2023). Sentiment classification of annual reports in Slovak language using symbolic, subsymbolic and statistic methods. *Procedia Computer Science*, *225*, 3508–3516. https://doi.org/10.1016/j.procs.2023.10.346

Koyyada, S. P., & Singh, T. P. (2022). A multi stage approach to handle class imbalance: An ensemble method. *Procedia Computer Science*, *218*, 2666–2674. https://doi.org/10.1016/j.procs.2023.01.239

KP, V., AB, R., HL, G., Ravi, V., & Krichen, M. (2024). A tweet sentiment classification approach using an ensemble classifier. *International Journal of Cognitive Computing in Engineering*, *5*, 170–177. https://doi.org/10.1016/j.ijcce.2024.04.001

Kristóf, T., & Virág, M. (2022). EU-27 bank failure prediction with C5.0 decision trees and deep learning neural networks. *Research in International Business and Finance*, *61*. https://doi.org/10.1016/j.ribaf.2022.101644

Liu, Z., Zhang, Z., Yang, H., Wang, G., & Xu, Z. (2023). An innovative model fusion algorithm to improve the recall rate of peer-to-peer lending default customers. *Intelligent Systems with Applications*, *20*. https://doi.org/10.1016/j.iswa.2023.200272

Mao, Y., Liu, Q., & Zhang, Y. (2024). Sentiment analysis methods, applications, and challenges: A systematic literature review. In *Journal of King Saud University - Computer and Information Sciences* (Vol. 36, Issue 4). King Saud bin Abdulaziz University. https://doi.org/10.1016/j.jksuci.2024.102048

Matrane, Y., Benabbou, F., & Sael, N. (2023). A systematic literature review of Arabic dialect sentiment analysis. In *Journal of King Saud University - Computer and Information Sciences* (Vol. 35, Issue 6). King Saud bin Abdulaziz University. https://doi.org/10.1016/j.jksuci.2023.101570

Mian, Z., Deng, X., Dong, X., Tian, Y., Cao, T., Chen, K., & Jaber, T. Al. (2024). A literature review of fault diagnosis based on ensemble learning. *Engineering Applications of Artificial Intelligence*, *127*. https://doi.org/10.1016/j.engappai.2023.107357

Mienye, I. D., & Sun, Y. (2022). A Survey of Ensemble Learning: Concepts, Algorithms, Applications, and Prospects. In *IEEE Access* (Vol. 10, pp. 99129–99149). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/ACCESS.2022.3207287

Mohammed, A., & Kora, R. (2022). An effective ensemble deep learning framework for text classification. *Journal of King Saud University - Computer and Information Sciences*, *34*(10), 8825–8837. https://doi.org/10.1016/j.jksuci.2021.11.001

Okoro, E. E., Obomanu, T., Sanni, S. E., Olatunji, D. I., & Igbinedion, P. (2022). Application of artificial intelligence in predicting the dynamics of bottom hole pressure for under-balanced

drilling: Extra tree compared with feed forward neural network model. *Petroleum*, *8*(2), 227–236. https://doi.org/10.1016/j.petlm.2021.03.001

Pattnaik, D., Ray, S., & Raman, R. (2024). Applications of artificial intelligence and machine learning in the financial services industry: A bibliometric review. *Heliyon*, *10*(1). https://doi.org/10.1016/j.heliyon.2023.e23492

Priyambada, S. A., Usagawa, T., & ER, M. (2023). Two-layer ensemble prediction of students' performance using learning behavior and domain knowledge. *Computers and Education: Artificial Intelligence*, *5*. https://doi.org/10.1016/j.caeai.2023.100149

Schmitt, M. (2023). Automated machine learning: AI-driven decision making in business analytics. *Intelligent Systems with Applications*, *18*. https://doi.org/10.1016/j.iswa.2023.200188

Sharma, D., Kumar, R., & Jain, A. (2022). Breast cancer prediction based on neural networks and extra tree classifier using feature ensemble learning. *Measurement: Sensors*, *24*. https://doi.org/10.1016/j.measen.2022.100560

SUDHAMATHI, T., & Perumal, K. (2024). ENSEMBLE REGRESSION BASED EXTRA TREE REGRESSORFOR HYBRID CROP YIELD PREDICTION SYSTEM. *Measurement: Sensors*, 101277. https://doi.org/10.1016/j.measen.2024.101277

Sun, Z., Harit, A., Cristea, A. I., Wang, J., & Lio, P. (2023). MONEY: Ensemble learning for stock price movement prediction via a convolutional network with adversarial hypergraph model. *AI Open*, *4*, 165–174. https://doi.org/10.1016/j.aiopen.2023.10.002

Tiwari, D., Nagpal, B., Bhati, B. S., Mishra, A., & Kumar, M. (2023). A systematic review of social network sentiment analysis with comparative study of ensemble-based techniques. *Artificial Intelligence Review*, *56*(11), 13407–13461. https://doi.org/10.1007/s10462-023-10472-w

Uddin, N., Uddin Ahamed, M. K., Uddin, M. A., Islam, M. M., Talukder, M. A., & Aryal, S. (2023). An ensemble machine learning based bank loan approval predictions system with a smart application. *International Journal of Cognitive Computing in Engineering*, *4*, 327–339. https://doi.org/10.1016/j.ijcce.2023.09.001

Umer, M., Sadiq, S., karamti, H., Abdulmajid Eshmawi, A., Nappi, M., Usman Sana, M., & Ashraf, I. (2022). ETCNN: Extra Tree and Convolutional Neural Network-based Ensemble Model for COVID-19 Tweets Sentiment Classification: ETCNN: COVID-19 Tweets Sentiment Classification. *Pattern Recognition Letters*, *164*, 224–231. https://doi.org/10.1016/j.patrec.2022.11.012

Wang, M., & Ji, H. (2022). Research on a Risk Control Model Based on Selective Ensemble Algorithm of Hierarchical Clustering and Simulated Annealing. *Procedia Computer Science*, *202*, 164–171. https://doi.org/10.1016/j.procs.2022.04.023

Wang, Y., Zhang, Y., Liang, M., Yuan, R., Feng, J., & Wu, J. (2023). National student loans default risk prediction: A heterogeneous ensemble learning approach and the SHAP method. *Computers and Education: Artificial Intelligence*, *5*. https://doi.org/10.1016/j.caeai.2023.100166

Widodo, A. O., Setiawan, B., & Indraswari, R. (2024). Machine Learning-Based Intrusion Detection on Multi-Class Imbalanced Dataset Using SMOTE. *Procedia Computer Science*, *234*, 578–583. https://doi.org/10.1016/j.procs.2024.03.042

Xiao, P., Liu, Z., Zhao, G., & Pan, P. (2024). Novel stacking models based on SMOTE for the prediction of rockburst grades at four deep gold mines. *Underground Space*. https://doi.org/10.1016/j.undsp.2024.03.004