# Optimized and Comprehensive Fake Review Detection based on Harris Hawks optimization integrated with Machine Learning Techniques

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**Abstract**

Fake review detection, often known as spam review detection, is a crucial aspect of natural language processing. It involves extracting valuable information from text documents obtained from various sources. Various methodologies, such as simple rule-based approaches, lexicon-based methods, and advanced machine learning algorithms, have been extensively employed with diverse classifiers to provide accurate detection of fake reviews. Nevertheless, review classification based on lexicons continues to face challenges in achieving high accuracies, mostly because of the need for domain-specific comprehensive dictionaries. Furthermore, machine learning-driven review detection also addresses the limitations in accuracy caused by the uncertainty of features in social data. In order To address the problem of accuracy, one effective approach is to carefully choose the most optimal set of features and minimize the number of features used. The Objective of the research paper is to select a small subset of features out of the thousands of features for accurate classification of spam review detection. Therefore, a good feature selection method is needed in order to speed up the processing rate and predictive accuracy. This paper, Harris Hawks Optimization (HHO), is utilized for feature selection in sentiment analysis tasks. The performance of the selected feature subsets was evaluated using SVM, X-GBoost, ETC classifiers. Experimental results on tweet reviews for the airline dataset demonstrated superior sentiment classification capabilities, achieving an accuracy of 0.9435% with SVM and 0.9607%, 0.9635% for X-Boost, ETC, respectively.

**Keywords**: Fake reviews detection; HHO; Feature selection; SVM; X_GBoost; ETC

## 1. Introduction

The proliferation of social media platforms has provided individuals with the opportunity to publicly participate and express their ideas [1]. Consequently, online reviews have become more prevalent. Some of these reviews intentionally mislead readers or opinion mining systems, either by giving undeserved positive reviews to certain entities to promote their products or by giving unfair or harmful negative reviews to other entities to damage their reputation. Incorrect reviews are also referred to as fake or false reviews. Extracting meaningful features from text data is crucial for various natural language processing tasks such as sentiment analysis, document classification, and information retrieval [2]. Feature selection plays a vital role in fake review detection as it helps to identify the most relevant and informative features while discarding redundant or irrelevant ones[3]. Given the growing frequency of fraudulent reviews across different online platforms, there is an urgent requirement for reliable and streamlined approaches to identify and detect them.The aim of opinion mining [4] is to obtain the user's attitude, feelings, or opinion of the type of review or comment provided by them. The opinions given to others help to make decisions easier. The implementation of a feature selection (FS) process in text analysis is crucial as it aids in the identification of the most significant and relevant elements [5]. This helps improve the overall performance and computational efficiency of text analysis algorithms. Furthermore, FS helps to reduce the curse of dimensionality by selecting a



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subset of features that are most relevant to the task at hand. The complexity of this problem increases exponentially, creating challenges in finding a solution, particularly when dealing with datasets that have several properties. The swarm intelligence algorithm utilized in FS was recently devised as method for detection. The Harris Hawks optimization (HHO) algorithm is one of swarm intelligence and an innovative a inspired by nature , and has shown superior performance enhancement in various optimization problems due to its efficient structure and limited parameters. HHO is a flexible and adaptable technique to various challenges, according to sources [6].HHO uses advanced heuristics to deal with data, including the detection of unnecessary and overlapping data, which improves the quality of results in classifying fake reviews. The strategies used in HHO, especially in the field of big data, show great ability to reduce dimensions, which contributes to improving the accuracy of classifying fake reviews, indicating the importance of its applications in improving and adapting computational models to meet new challenges in this field. The main contribution of this paper is

1. Employing effective pre-processing techniques allows for the elimination of irrelevant elements that do not contribute to the identification of fraudulent reviews.
2. A hybrid feature extraction methodology, which combines TF-IDF with FastText, will be employed to facilitate the extraction of important and relevant features.
3. Data Balancing: The implementation of the Synthetic Minority Over-sampling Technique (SMOTE) aids in achieving a more equitable distribution of classes, hence ensuring fair treatment of all classes and preventing models from neglecting the under-represented class.
4. Utilizing Swarm Intelligence techniques to enhance the precision and efficiency of the classification process by selecting a subset of features from the original feature set and reducing the time required for analysis.

## 2. Related Work

The widespread use of Twitter, which facilitates connections between millions of individuals worldwide, has ultimately established it as a popular and prominent source of sentiment-rich data. Various feature selection techniques. The study by Kumar and Jaiswal [7] in 2019 used swarm intelligence for improved sentiment analysis accuracy on Twitter. They use binary grey wolf and binary moth flame algorithms to evaluate performance on two benchmark datasets.with binary grey wolf optimizing the support vector machine to the highest accuracy of 76.5%. In 2019, [8] T. Anuprathibha and C. S. Kanimozhiselvi used Natural Language Processing (NLP) to extract features from tweet data, using the Penguin Search Optimization (PeSOA) algorithm to classify drugs and cancer keywords. The combined PeSOA-SVM method achieved accuracy, precision, recall, and F-Measure values, with accuracy rates of 79.5% and 79.7%, respectively. S. Radha Priya and M. Devapriya. [9], In 2020, This research aims to determine the most efficient machine learning algorithm for analyzing adverse drug reactions (ADR) associated with Metformin, a diabetic medication. Glowworm Swarm Optimization (GSO) is used for optimal feature selection and is integrated with Naïve Bayes (NB), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM). The experimental results show that the combination of GSO and SVM achieves a maximum accuracy of 94%. Saad's (2020) study [10] utilizes six machine learning algorithms, including SVM, logistic regression, random forest, XGBoost, naive Bayes, and decision trees. Features were extracted utilizing Bag-of-Words (BOW) technology. The study on Twitter data from US airlines, which categorized sentiments into positive, negative, and neutral categories, showed that Support Vector Machines (SVM) achieved the greatest accuracy rate of 83.31.Elmogy, Ahmed M. et al. [11], In 2021, Researchers utilized engineering techniques in machine learning to identify fraudulent reviews, extract relevant characteristics from the reviews, and analyze a genuine dataset of restaurant evaluations that did not include user behavior-derived attributes. The employed approaches were Logistic Regression (LR), Naive Bayes (NB), K-Nearest Neighbors (KNN), and Support Vector Machines (SVM). M. Imani and S. Noferesti. [12], In 2022, the suggested technique demonstrates the capability to accurately identify several aspects of the test set with a 74.4% F-measure. Furthermore, it surpasses the performance of the current aspect extraction methods. Additionally, by training the random forest classifier on the dataset created through distant supervision, an F-measure of 73.96% was achieved. Furthermore, utilizing this dataset to fine-tune BERT for aspect classification resulted in a higher F-measure (78.05%) compared to an existing method that involved training the random forest classifier on a manually constructed dataset with high accuracy. Y. Abdul Hammed and P. J. Karim. [13], In 2022 used Twitter-API to compile tweets about Biden, Benzema, Apple, and NASA. They extracted features using various models, including Doc2Vec (Bow, DMC, and DMM), TF-IDF, and the Shark Smell Optimizer method. The SVM parameters were optimized using the SSO approach, resulting in a precision of 92.12%, surpassing the highest precision of 88.69% achieved without optimization. In 2023, A. M. Asri, S. R. Ahmad, and N. M. M. Yusop [14] proposed a technique for conducting perceptive sentiment analysis (FS) by collecting data on the multiple potential solutions created by the PSO algorithm. The objective of the research is to determine the most precise subset of drug reviews that can enhance the classification of sentiment analysis. Based on the experimental findings, The performance of PSO in terms of classification exceeded that of ant colony optimization and a genetic algorithm. The algorithm achieved an average



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of precision 49.3%, recall of 73.6%, F-score of 57.2%, and accuracy of 57.2%. Shiramshetty Gouthami and Nagaratna P. Hegde. [15], In 2023, An over-sampling methodology was developed to improve accuracy in the misclassification of minority classes in tweets. The model classifies tweets based on sentiment, excluding special characters, URLs, and stop words. It converts tweets into feature vectors using the Bag of Words model and uses Random Forest and Recurrent Neural Network classification models to categorize tweets based on sentiment. The system effectively categorizes tweets as favorable, negative, or neutral. The density-based SMOTE results show the effectiveness of the methodology, with the TFIDF vectorizer Random Forest model achieving an accuracy of 81% and an F1 score of 70%.Shiramshetty Gouthami and Nagaratna P. Hegde [16], in 2024, developed an ensemble method for sentiment analysis to detect fraudulent reviews. In evaluating the performance of the ensemble model, accuracy served as the primary metric where the ensemble model, which combines SVM, KNN, and decision tree classifiers with BERT for feature extraction, achieved a leading accuracy of 80% in detecting fake reviews. Notably, the combination of KNN with BERT closely followed, securing an accuracy rate of 78%. Table 1 illustrates the summarization of related works.

**Table 1:** Summarize of related works

| Ref & Year | Dataset | Feature Extraction | Feature Selection | Classifier Results |
|---|---|---|---|---|
| [7] 2019 | Twitter Data | TF-IDF | Binary grey wolf and binary moth flame | Accuracy of Binary grey wolf with<br>NB 38 %<br>DT 63.9 %<br>SVM 76.5 %<br>MLP 67.9 %<br>k-NN 63.2 % |
| | | | | Accuracy of Binary moth flame with<br>NB 40.3 %<br>DT 64.9 %<br>SVM 74.8 %<br>MLP 70.2 %<br>k-NN 65.9 % |
| [8] 2019 | Tweets on cancer and drugs. | POS, content words. | Penguin search optimization algorithm (PeSOA). | Cancer dataset<br>KNN 78.5 %<br>NB 78.8 %<br>SVM 79.5 % |
| | | | | Drug dataset<br>KNN 79.2%<br>NB 79.4 %<br>SVM 79.7 % |
| [9] 2020 | Twitter | TF-IDF, Bows. | GSO | Accuracy<br>NB 91%<br>KNN 92%<br>SVM 94% |
| [10] 2020 | Twitter US Airline Sentiment. | BOW. | Not mentioned | Accuracy<br>SVM 83.31%.<br>LR 81.81%<br>RF 78.55%<br>X_GBoost 75.93%<br>NB 73%<br>DT 70.51% |
| [11] 2021 | Yelp | TF-IDF, N-gram. | caps-count, punch-count, emojis behavioral, “Group by” function. | Accuracy<br>KNN 86.89%<br>NB 86.08%<br>SVM 86.23%<br>LR 86.9%<br>RF 86.82% |
| [12] 2022 | Drug reviews. | POS, BOW, Semantic group, and descriptive words. | Vector Related Words (RW). | (BERT)<br>F-measure 78.05% |
| [13] 2022 | Tweets of Biden, Benzema, Apple, and NASA. | Doc2Vec(DBoW, DMC, and DMM), TF-IDF. | SSO Algorithm. | Accuracy<br>SVM<br>NASA(DMM)<br>90.01<br>Apple(Bow)<br>90.95<br>Benzema(TF-IDF)<br>81.59<br>Biden(TF-IDF)<br>77.21 |
| [14] 2023 | Drug reviews. | TF-IDF, POS, and Text Blob. | ACO, GA, and PSO. | KNN accuracy with<br>ACO 53%<br>GA 54% |



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|---|---|---|---|---|
| | | | | PSO 58% |
| [15] 2023 | Twitter airline | Count Vectorizer, TF-IDF. | _____ | Accuracy<br>RNN 0.76%<br>RF with Count Vectorizer 0.78%<br>RF with TF-IDF Vectorizer 0.82% |
| [16] 2024 | Separate CSV files for different product reviews. Concatenated all these CSV files into one comprehensive dataset. | Word2Vec, TF-IDF, and BERT. | _____ | Accuracy<br>RF 0.73%<br>DT 0.78%<br>LR 0.75%<br>SVM 0.78%<br>NB 0.68%<br>KNN 0.78%<br>Ensemble(RF,DT,KNN) 0.80% |

## 3. Harris Hawks Optimization (HHO)

The HHO optimization algorithm is applied to identify the optimized feature subset. That will improve the performance of classifiers in terms of runtime and accuracy. HHO can be defined as a unique optimizer that is inspired by the chain of reactions and actions used by rabbits and hawks during their hunting activity. The fundamental mathematical base of this optimizer, as outlined in the original HHO article, enables it to be highly effective in addressing a wide range of unconstrained and constrained problems. The search engine optimizer incorporates two exploration stages and four exploitation phases to update the agents, as shown in Figure 1 [16]. The quality of findings is enhanced by integrating many time-varying mechanisms using the greedy technique. It improves the quality of findings by combining numerous time-varying mechanisms with the greedy approach. The steps of HHO are described in Algorithm1.

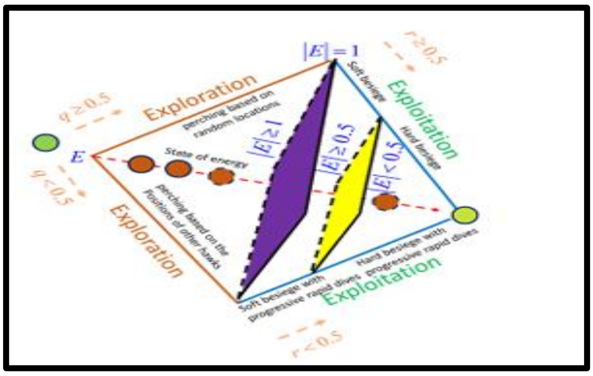


**Figure 1.** Different stages of HHO

Algorithm 1: Pseudocode of Harris Hawks Optimization [17]

Input: T and N
Output: Xrabbit

Random initialization of population: H random hawks xi (i=1,2,3,….., H)
While the stop condition is not met:
Compute the fitness values
Set Xrabbit as the optimal solution
For each hawk (Xi):
Update E according to the equation: $\boldsymbol{E} = \mathbf{2}\boldsymbol{E}\ (\mathbf{1} - \boldsymbol{t})\ \mathbf{0} \backslash t\boldsymbol{T}$
Update (E0, J)
If |E| ≥ 1:
Update the location vector according to the equation:
If $q \geq 0.50$oneX⃗→ (t+1)= $\mathbf{Xrand(t)} - \mathbf{r1}|\mathbf{Xrand(t)} - \mathbf{2r2X(t)}|$
If $q < 0.50$
X⃗→ (t+1)= $(X_{rabbit}(t) - X_m(t)) - r_3 (LB + r_4 (UB - LB))$

If |E| < 1
If |E| ≥ 0.50 & r ≥0.50:
Update the location vector using the equation:
$\mathbf{X(t + 1) = \Delta X(t) - E|JxXrabbit\ (t) - X(t)|}$
Elseif r ≥0.50 & |E| < 0.50:
One Update the location vector using the equation:: $\mathbf{X\ (t+1)\ = Xrabbit(t) - E|\Delta X(t)|}$
Elseif r <0.50 & |E| ≥ 0.50:
r using the equation: $\mathbf{X(t + 1) = Y, if\ f(Y) < F(X(t))\ \{\ , if\ f(Z) < F(X(t))\ Z}$
Elseif r <0.50 & |E| < 0.50 Update the location vector using the equation: $\mathbf{X(t + 1) = Y\ , if\ f(Y) < F(X(t))\ \{\ , if\ f(Z) < F(X(t))\ Z}$
Return Xrabbit



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## 4. Proposed Methodology

Figure 2 shows the general structure of the proposed system, which consists of the following stages that will be explained in sequence: pre-processing, feature extraction, data balancing, feature selection, and finally the review classification stage using machine learning algorithms.

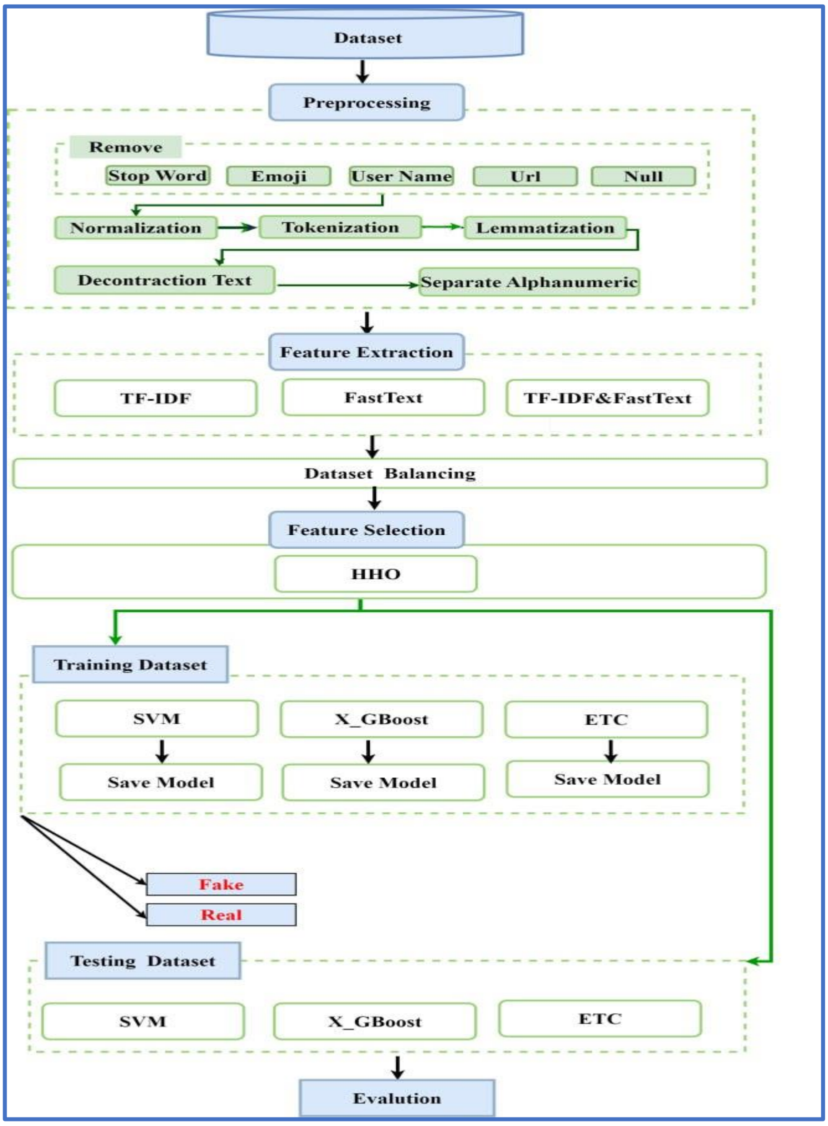


**Figure 2.** Diagram of fake reviews detection system

### 4.1 Dataset

The Kaggle dataset "CrowdFlower Twitter US Airline Sentiment" was used to analyze sentiment values in 14,640 tweets from six major airlines. The dataset [18] contains 2,363 positive values, 9,178 negative values, and 3,099 neutral values, with explanations for negative classification and confidence levels. Key attributes included tweet id, sentiment, sentiment confidence score, negative reason, airline, sentiment gold, name, retweet count, tweet text, tweet coordinates, time of the tweet, date of the tweet, tweet location, and user time zone.

### 4.2 Preprocessing

It is a crucial step in many supervised learning approaches, as well as text mining[19]. The suggested system's preprocessing procedures are a crucial step in achieving excellent results. Some major preprocessing steps are converting to lowercase, tokenization, stop word removal, and lemmatization**.**



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A. Removal of punctuation: In order to preserve the integrity of the data, it is necessary to remove any instances of null, missing values, and special characters, such as punctuation, from the dataset; none of these factors are essential for opinion classification.
B. Normalization: This method merges several instances of the same letter by removing all symbols and digits and converting all characters to either uppercase or lowercase. Specified steps include: - Removing all numerical values. - Eliminating all symbols, including!?, #, $, @, *, [], {}, =, %, &, (), -, _, -, ", =, +, ', and /. - Transform each word to lowercase (LC).
C. Tokenization: It is a basic step in preprocessing, which is, in fact, a process of segmenting an entire raw text document into smaller parts, and each of these parts is known as a token.
D. Lemmatization: It denotes the process of Reducing the inflected and derived forms of a word to its base or stem of the word. In this lemmatization process, the term used to denote the original form of a word is called the lemma. This procedure is more accurate than the stem, which is not reliant on dictionary definitions.
E. DE contraction text: Expanding contractions in text data ensures consistency in analysis by converting shortened forms to their full forms. For instance, "can't" can be expanded to "cannot" to maintain uniformity and accuracy in natural language processing tasks.
F. Separate alphanumeric: Separating alphanumeric characters into separate entities improves text data analysis and processing. For instance, in the example given, the original text is "The price of the product is $99.99, and it received a 5-star rating." The resulting text is "$ 99.99," and the "5-star" rating is "5-star." This separation enhances clarity and facilitates better analysis of text data.

### 4.3 Feature Extraction

The research addresses the difficulty of accurately and efficiently extracting features from input reviews for fake review detection. A hybrid feature extraction methodology (TF-IDF &FastText) is proposed to get a high level of accuracy. This entails utilizing several algorithms. To determine the relevance or uniqueness of a word in a document relative to a collection of documents. It is a metric used to determine the relevance or uniqueness of a word in a document relative to a collection of documents[20]. Term frequency is the number of times a term appears in a document, while inverse document frequency quantifies the frequency of a word over every document. The FastText method captures morphological details by expressing words as vector sums of n-grams, with supplementary components for sub-words. FastText algorithm uses n-grams to create vector representations for words not in the lexicon, producing 300-dimensional token vectors for tweets. The integration of TF-IDF and Fasttext results in the representation of each processed review as a hybrid feature vector, hence guaranteeing accurate, high-quality review categorization.

### 4.4 Data Balancing

Class imbalance refers to an uneven distribution of data between classes, which can lead to biased behavior in machine learning models. SMOTE is a synthetic oversampling technique that aims to address class imbalance by generating synthetic examples for the minority class. Instead of simply replicating existing instances, SMOTE selects minority class examples and creates synthetic instances along line segments connecting their nearest neighbors. By oversampling the minority class, SMOTE helps create a more balanced class distribution, ensuring fair treatment of all classes and preventing models from ignoring the under-represented class [21].

### 4.5 Feature Selection

Feature selection is a crucial stage in data analysis, to identify a subset of features from the entire set of retrieved features to decrease the problem size that learning algorithms handle. This helps improve classification accuracy by reducing computational demands and enhancing the efficiency of the classification process by reducing the size of the training data used to train the model [17]. This paper utilized the Harris Hawks Optimization (HHO) algorithm as the feature selection strategy, along with the Support Vector Machine (SVM) as the classification methodology, where the classification algorithm is treated as a "black box" for the feature selection process. The performance of the classification algorithm is used as an evaluation function to rank feature subsets and guide the search.

### 4.6 Evaluation Metrics

Accuracy, F1, precision, recall, and TT(Sec) have been considered to evaluate the effectiveness of applying feature selection using HHO on our model. The formulas are expressed as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$



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where TP, TN, FP, and FN indicate true positive, true negative, false positive, and false negative, respectively.

$$F1 = 2 * \frac{((TP/(TP+FP)*(TP/(TP+FN))}{((TP/(TP+FP)+(TP/(TP+FN))} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

$$TT(SEC) = End\ Time - Start\ Time \quad (5)$$

TT(SEC) is a critical performance metric that assesses a system's speed in analyzing and categorizing reviews, especially for real-time applications. It calculates the difference between start and end times of processing operations

## 5. Experiment Result

This section includes experimental results that specifically demonstrate the importance of implementing preprocessing operations, hybrid feature extraction method (TF-IDF and FastText), and HHO feature selection after data balancing for sentiment classification on 80% training, 20% testing of the Twitter US Airline Sentiment dataset. Table 2 shows the performance of classification algorithms with accuracy and time required for the Twitter US Airline Sentiment dataset when using hybrid feature extraction method (TF-IDF and FastText). Table 3 shows the performance evaluation of classification algorithms using performance evaluation parameters Accuracy, Precision, Recall, F1_Score, and TT(Sec) after applying HHO algorithm as feature selector.

**Table 2:** Accuracy results for feature extraction

| Classifier | TF-IDF | FastText | Hybrid (TFIDF and Fasttext) | TT(Sec) |
|---|---|---|---|---|
| LightGBM | 0.8819 | 0.9186 | 0.9264 | 0.0109 |
| XGBoost | 0.8899 | 0.9437 | 0.9264 | 0.0167 |
| ET | 0.9206 | 0.9478 | 0.9284 | 0.1503 |

**Table 3:** The accuracy, precision, recall, F1, and TT(Sec) using HHO

| Classifier | Accuracy | Precision | Recall | F1 | TT(Sec) |
|---|---|---|---|---|---|
| LightGBM | 0.9540 | 0.9538 | 0.9539 | 0.9538 | 0.1206 |
| XGBoost | 0.9576 | 0.9575 | 0.9575 | 0.9575 | 0.0813 |
| ET | 0.9578 | 0.9578 | 0.9578 | 0.9578 | 0.3821 |

The above results illustrate that the ETC classifier has the best performance when compared to other ML Algorithms, Extra Trees is a more efficient method than XGBoost in certain situations due to its ability to handle residual noise and subtleties in text data. ETC's high randomness prevents overfitting and improves generalization, allowing it to handle subtle variations in expression and linguistic errors. XGBoost, while powerful in handling complex data, can be sensitive to residual noise after preprocessing, especially in environments with linguistic variation or unstructured noise that may not be fully addressed during preprocessing. figure 3 shows the confusion matrix of the ETC classifier.

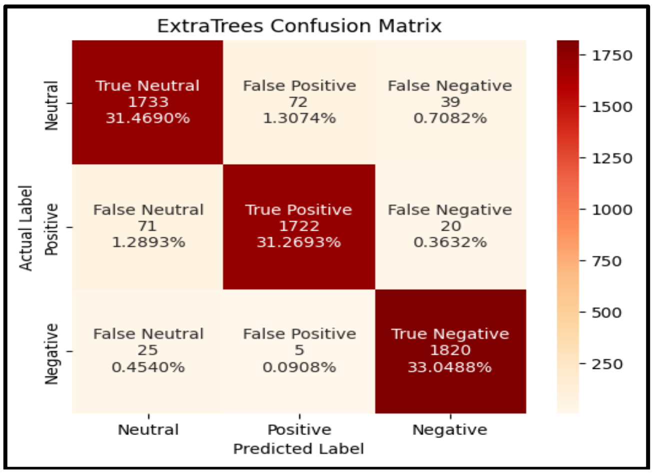


**Figure 3.** Confusion Matrix for HHO+ET



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Based on the confusion matrix, the classification model showed high classification accuracy, correctly classifying 1,733 neutral tweets, 1,722 positive tweets, and 1,820 negative tweets. However, 72 neutral tweets were classified as positive, 39 neutral tweets as negative, 71 positive tweets as neutral, and 20 positive tweets as negative. In addition, 25 negative tweets were classified as neutral, and 5 negative tweets were classified as positive. Considering these numbers, it can be said that the model achieved an overall accuracy of about 95.79%, reflecting good performance with a small percentage of incorrect classifications (about 4.21%), indicating that the model could be improved to reduce these errors. Figure 4 shows the effectiveness of applying a hybrid feature extraction approach, and in order to enhace the performance HHO is applied resulting in an accuracy and time analysis improvement.

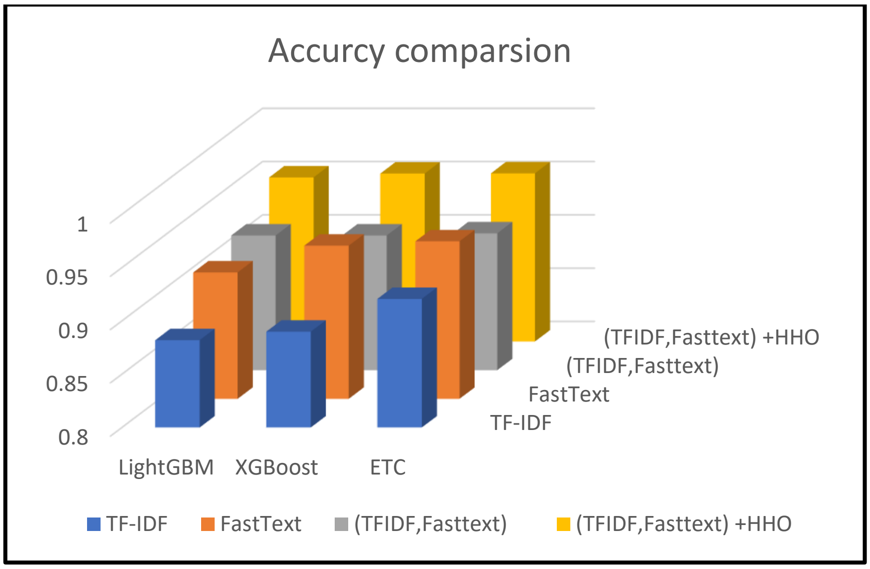


**Figure 4.** Accuracy using hybrid (TFIDF, Fasttext) vs. hybrid (TFIDF, Fasttext) +HHO prediction

## 6. Comparison of Previous Works

This section presents a comparison between the existing work and our proposed system for the same (just using a hybrid feature extraction) and different datasets (applying feature selection using HHO)

**Table 4:** Comparison of previous works for the same dataset

| Ref & Year | Feature Extraction | Classifier | Results |
|---|---|---|---|
| 2020 [22] | Bag of Words | SVM | 83.31 |
| [9] 2020 | BOW. | SVM , LR , RF, X_GBoost, NB ,and DT. | Accuracy SVM 83.31%. LR 81.81% RF 78.55% X_GBoost 75.93% NB 73% DT 70.51% |
| 2020 [23] | TF-IDF, Word2vect. | LR, RF, SGDC, SV, LR + SGDC, LSTM, and CNN-LSTM. | Accuracy 91%. |
| 2021 [24] | Metadata + TFIDF + trainable Embedding. | DNN+CNN | Accuracy 91%. |
| 2021 [25] | Bagging classifiers, non-bagging Classifiers. | LR, RF, NB, DTC, SVC, and SGDC. | LR accuracy 77,27%. |
| 2021 [26] | 1 Vector of numbers with Kera's embedding. | LR, DT, NB, SVM, LSTM, CNN ,and CNN-LSTM. | CNN-LSTM accuracy 90.2, 91.3% |



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| | | | |
|---|---|---|---|
| 2022 [27] | Bag of words, TF-IDF. | SVM, LR, RF,and NB. | RF accuracy is 92.39%. |
| 2022 [28] | Bag of words, TF-IDF | LR, DNN. | DNN accuracy 89% |
| 2023 [29] | Negative comments, a word cloud, and a bar graph. NLP tasks: MLM and SP | LG,KNN,NB, SVM, DT, RF, BERT. | The best classification model is BERT, with an accuracy of 83% |
| [14] 2023 | Count Vectorizer, TF-IDF. | RNN, RF. | Accuracy<br>RNN<br>0.76 %<br>RF with Count Vectorizer<br>0.78 %<br>RF with TF-IDF Vectorizer<br>0.82 % |
| Proposed system | A hybrid (TF_IDF&FastText) | SVM, X_GBoost, and ETC. | SVM<br>0.91%<br>X_GBoost 0.95%<br>ETC<br>0.95% |

The above results illustrate that our proposed hybrid feature extraction has the best performance when compared to other previous works. Even without applying feature selection. Table 5 illustrates that applying feature selection using HHO has the best performance when compared to other previous works utilizing other feature selection algorithms.

**Table 5:** Comparison of previous works for different datasets

| Ref & Year | Dataset | Feature Extraction | Feature Selection | Classifier Results |
|---|---|---|---|---|
| [5] 2019 | Integrating Biology and the Bedside (i2b2) data set | UMLS | PSO | Accuracy<br>NB 78.66 %<br>LSVM 88.93 %<br>KNN 89.33 %<br>DT 92.25 %<br>LR 89.33 % |
| [6] 2019 | Twitter Data | TF-IDF | Binary grey wolf and binary moth flame | Accuracy of Binary grey wolf with<br>NB 38 %<br>DT 63.9 %<br>SVM 76.5 %<br>MLP 67.9 %<br>k-NN 63.2 %<br><br>Accuracy of Binary moth flame with<br>NB 40.3 %<br>DT 64.9 %<br>SVM 74.8 %<br>MLP 70.2 %<br>k-NN 65.9 % |
| [7] 2019 | Tweets on cancer and drugs. | POS, content words. | Penguin search optimization algorithm (PeSOA). | Cancer dataset<br>KNN 78.5 %<br>NB 78.8 %<br>SVM 79.5 %<br><br>Drug dataset<br>KNN 79.2%<br>NB 79.4 %<br>SVM 79.7 % |
| [8] 2020 | Twitter | TF-IDF, Bows. | GSO | Accuracy<br>NB 91%<br>KNN 92%<br>SVM 94% |



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| | | | | |
|---|---|---|---|---|
| [10] 2021 | Yelp | TF-IDF, N-gram. | caps-count, punch-count, emojis behavioral, “Group by” function. | Accuracy<br>KNN 86.89%<br>NB 86.08%<br>SVM 86.23%<br>LR 86.9%<br>RF 86.82% |
| [11] 2022 | Drug reviews. | POS, BOW, Semantic group, and descriptive words. | Vector Related Words (RW). | (BERT)<br>F-measure<br>78.05% |
| [12] 2022 | Tweets of Biden, Benzema, Apple, and NASA. | Doc2Vec(DBoW, DMC, and DMM), TF-IDF. | SSO Algorithm. | Accuracy<br>SVM<br>NASA(DMM)<br>90.01<br>Apple(Bow)<br>90.95<br>Benzema(TF-IDF)<br>81.59<br>Biden(TF-IDF)<br>77.21 |
| [13] 2023 | Drug reviews. | TF-IDF, POS, and Text Blob. | ACO, GA, and PSO. | KNN accuracy with<br>ACO 53%<br>GA 54%<br>PSO 58% |
| [15] 2024 | Separate CSV files for different product reviews. Concatenated all these CSV files into one comprehensive dataset. | Word2Vec, TF-IDF, and BERT. | ——— | Accuracy<br>RF 0.73%<br>DT 0.78%<br>LR 0.75%<br>Ensemble<br>(RF,DT,LR) 0.75%<br>SVM 0.78%<br>NB 0.68%<br>KNN 0.78%<br>Ensemble(RF,DT,LR) |
| Proposed system | Twitter US airline | Hybrid(TF-IDF and FastText) | HHO | SVM<br>0.94<br>X_GBoost<br>0.96<br>ETC<br>0.96 |

## 7. Conclusion and Future work

To distinguish between fake and real tweet reviews on the American Airlines dataset, this paper used powerful preprocessing steps that had the effect of eliminating the useless elements in the classification process, in addition to using hybrid feature extraction techniques (TF-IDF and FastText). To improve the performance quality and help in identifying fake reviews, the Harris Hawks Swarm Intelligence algorithm is applied as a feature selector to different classifiers. The ET classifier has the highest accuracy of 0.9578%, while LightGBM has the lowest accuracy of 0.9540%. To improve the performance of the proposed system for future projects, there are several tactics, including taking advantage of additional preprocessing steps, different feature extraction methods, using a hybrid feature extraction approach, applying different swarm algorithms, or applying a hybrid of these algorithms to improve the feature selection process, along with different classifiers such as Extreme Learning Machine (ELM), AdaBoost classifier, and Random Forest, and also aiming to reduce the analysis time to real time.

## References

[1] P. Akhtar *et al.*, “Detecting fake news and disinformation using artificial intelligence and machine learning to avoid supply chain disruptions,” *Ann. Oper. Res.*, pp. 633–657, 2022, doi: 10.1007/s10479-022-05015-5.
[2] A. M. Elmogy, U. Tariq, and A. Ibrahim, “Fake Reviews Detection using Supervised Machine Learning,” vol. 12, no. 1, pp. 601–606, 2021.
[3] “View of Comparative Analysis of MFO, GWO and GSO for Classification of Covid-19 Chest X-Ray Images.pdf.”
[4] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, “Harris hawks optimization: Algorithm and applications,” *Futur. Gener. Comput. Syst.*, vol. 97, pp. 849–872, 2019, doi: 10.1016/j.future.2019.02.028.



DOI: https://doi.org/10.54216/JCIM.150102
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[5] M. Abdollahi, X. Gao, Y. Mei, S. Ghosh, and J. Li, "An Ontology-based Two-Stage Approach to Medical Text Classification with Feature Selection by Particle Swarm Optimisation," *2019 IEEE Congr. Evol. Comput. CEC 2019 - Proc.*, pp. 119–126, 2019, doi: 10.1109/CEC.2019.8790259.
[6] A. Kumar and A. Jaiswal, "Swarm intelligence based optimal feature selection for enhanced predictive sentiment accuracy on twitter," *Multimed. Tools Appl.*, vol. 78, no. 20, pp. 29529–29553, 2019, doi: 10.1007/s11042-019-7278-0.
[7] T. Anuprathibha and C. S. Kanimozhiselvi, "Penguin search optimization based feature selection for automated opinion mining," *Int. J. Recent Technol. Eng.*, vol. 8, no. 3, pp. 648–653, 2019, doi: 10.35940/ijrte.B2629.098319.
[8] S. R. Priya, "Twitter Sentiment Analysis with Diabetic Drugs Using Machine Learning Techniques with Glowworm Swarm Optimization Algorithm," vol. 9, no. 07, pp. 62–68, 2020.
[9] C. N. Dang, M. N. Moreno-García, and F. De La Prieta, "Hybrid Deep Learning Models for Sentiment Analysis," *Complexity*, vol. 2021, 2021, doi: 10.1155/2021/9986920.
[10] A. M. Elmogy, U. Tariq, A. Ibrahim, and A. Mohammed, "Fake Reviews Detection using Supervised Machine Learning," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 1, pp. 601–606, 2021, doi: 10.14569/IJACSA.2021.0120169.
[11] M. Imani and S. Noferesti, "Aspect extraction and classification for sentiment analysis in drug reviews," *J. Intell. Inf. Syst.*, vol. 59, no. 3, pp. 613–633, 2022.
[12] O. Y. Abdulhammed and P. J. Karim, "Sentiment Analysis using SVM-based SSO Intelligence Algorithm," *Passer J. Basic Appl. Sci.*, vol. 4, no. 02, pp. 17–39, 2022, doi: 10.24271/psr.2022.160801.
[13] A. M. Asri, S. R. Ahmad, and N. M. M. Yusop, "Feature Selection using Particle Swarm Optimization for Sentiment Analysis of Drug Reviews," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 5, pp. 286–295, 2023, doi: 10.14569/IJACSA.2023.0140530.
[14] S. Gouthami and N. P. Hegde, "Improving Sentiment Analysis on Imbalanced Airlines Twitter Data Using DSMOTE Technique," *SSRG Int. J. Electron. Commun. Eng.*, vol. 10, no. 9, pp. 38–51, 2023, doi: 10.14445/23488549/IJECE-V10I9P105.
[15] M. Periasamy, "Finding fake reviews in e-commerce platforms by using hybrid algorithms".
[16] A. I. Saad, "Opinion Mining on US Airline Twitter Data Using Machine Learning Techniques," *16th Int. Comput. Eng. Conf. ICENCO 2020*, pp. 59–63, 2020, doi: 10.1109/ICENCO49778.2020.9357390.
[17] W. Z. H. U. Dong-, "JOURNAL OF SOUTHWEST JIAOTONG UNIVERSITY USocial SciencesR," vol. 58, no. 1, pp. 1139–1149, 2011.
[18] M. R. Mandal, "An Advance Approach toward Sentiment Analysis using Swarm Intelligence," *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 9, no. VI, pp. 1710–1713, 2021, doi: 10.22214/ijraset.2021.35228.
[19] H. M. Alabool, D. Alarabiat, L. Abualigah, and A. A. Heidari, *Harris hawks optimization: a comprehensive review of recent variants and applications*, vol. 33, no. 15. Springer London, 2021. doi: 10.1007/s00521-021-05720-5.
[20] A. N. H. Zaied, M. Ismail, and S. El-Sayed, "A Survey on Meta-heuristic Algorithms for Global Optimization Problems," *J. Intell. Syst. Internet Things*, vol. 1, no. 2, pp. 48–60, 2020, doi: 10.54216/jisiot.010104.
[21] J. Park, S. Kwon, and S. P. Jeong, "A study on improving turnover intention forecasting by solving imbalanced data problems: focusing on SMOTE and generative adversarial networks," *J. Big Data*, vol. 10, no. 1, 2023, doi: 10.1186/s40537-023-00715-6.
[22] A. S. Issa, Y. H. Ali, and T. A. Rashid, "Comparative Analysis of Swarm Algorithms to Classification of covid19 on X-Rays," *2022 Int. Conf. Data Sci. Intell. Comput. ICDSIC 2022*, no. Icdsic, pp. 164–169, 2022, doi: 10.1109/ICDSIC56987.2022.10075733.
[23] S. By, "Asst. Prof. Dr. Samar Allouch 2023," 2023.
[24] A. Patel, P. Oza, and S. Agrawal, "Sentiment Analysis of Customer Feedback and Reviews for Airline Services using Language Representation Model," *Procedia Comput. Sci.*, vol. 218, pp. 2459–2467, 2022, doi: 10.1016/j.procs.2023.01.221.
[25] I. Journal, F. Technological, and A. Rai, "Us Airline Twitter Data on Sentiment Analysis Using Deep Neural Network," vol. 9, no. 8, pp. 1–9, 2022.
[26] J. R. Monalisha Sahoo, "Survey on Sentiment Analysis to Predict Twitter Data using Machine Learning and Deep Learning," *Int. J. Eng. Res. Technol.*, vol. 11, no. 7, pp. 506–512, 2022.
[27] P. K. Jain, V. Saravanan, and R. Pamula, "A Hybrid CNN-LSTM: A Deep Learning Approach for Consumer Sentiment Analysis Using Qualitative User-Generated Contents," *ACM Trans. Asian Low-Resource Lang. Inf. Process.*, vol. 20, no. 5, 2021, doi: 10.1145/3457206.
[28] M. V. K. Et.al, "Collaborative Classification Approach for Airline Tweets Using Sentiment Analysis," *Turkish J. Comput. Math. Educ.*, vol. 12, no. 3, pp. 3597–3603, 2021, doi: 10.17762/turcomat.v12i3.1639.
[29] K. M. Hasib, M. A. Habib, N. A. Towhid, and M. I. H. Showrov, "A Novel Deep Learning based Sentiment Analysis of Twitter Data for US Airline Service," *2021 Int. Conf. Inf. Commun. Technol. Sustain. Dev. ICICT4SD 2021 - Proc.*, pp. 450–455, 2021, doi: 10.1109/ICICT4SD50815.2021.9396879.
[30] M. Umer, I. Ashraf, A. Mehmood, S. Kumari, S. Ullah, and G. Sang Choi, "Sentiment analysis of tweets using a unified convolutional neural network-long short-term memory network model," *Comput. Intell.*, vol. 37, no. 1, pp. 409–434, 2021, doi: 10.1111/coin.12415.



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