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EVALUATING AI-DRIVEN MACHINE LEARNING ALGORITHMS FOR EFFECTIVE OPINION EXTRACTION FROM ONLINE CONTENT

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ABSTRACT
This paper evaluates the effectiveness of AI-driven machine learning algorithms for sentiment analysis, focusing on opinion extraction from online content. Sentiment analysis, a subset of Natural Language Processing (NLP), categorizes text based on the sentiment expressed by the author, providing valuable insights for businesses and researchers. We compare traditional classifiers—Naïve Bayes, k-Nearest Neighbor, and Random Forest—with neural network classifiers—LVQ, Elman, and FFNN. A novel neural network algorithm, KINN, incorporating genetic optimization, is introduced to enhance classification accuracy. Using data from Kaggle and student feedback on M-Learning systems, our experiments demonstrate that the KINN algorithm significantly improves sentiment classification accuracy, reaching up to 83.33%. This research highlights the potential of advanced AI techniques in refining sentiment analysis for practical applications.

Keywords: KINN, FFNN, NLP, AI, and GKINN

INTRODUCTION
Sentiment analysis, a subset of NLP, focuses on identifying and extracting subjective information from text. It involves categorizing text as positive, negative, or neutral based on the sentiment expressed by the author. This process is particularly valuable for understanding consumer feedback and monitoring public opinion on various topics.

The Role of AI in Sentiment Analysis
AI enhances sentiment analysis by applying complex mathematical models to data processed by NLP. These models can detect subtle nuances in language that traditional methods might miss. AI-based sentiment analysis tools automatically extract opinions, sentiments, and emotions from text, providing insights that are essential for businesses and researchers.

Applications of Sentiment Analysis
Sentiment analysis has diverse applications:

- **Marketing**: Evaluating the success of advertising campaigns and product launches.
- **Customer Service**: Analyzing feedback to improve service quality.
- **Political Analysis**: Gauging public opinion on political issues and candidates.

By leveraging sentiment analysis, organizations can make informed decisions based on real-time data from multiple sources.

Challenges in Sentiment Analysis
Key challenges in sentiment analysis include:

- **Irony and Sarcasm Detection**: Detecting sarcastic remarks is difficult but crucial for accurate sentiment classification.
- **Language Variation**: Handling different languages, dialects, and slang requires robust, adaptable models.
- **Dynamic Sentiment**: Sentiments can change over time, necessitating models that can update and adapt to new data.

Addressing these challenges is essential for developing reliable sentiment analysis systems.

Evaluation of Machine Learning Algorithms

The evaluation of machine learning algorithms in sentiment analysis involves:

- **Accuracy**: The ability of the model to correctly classify sentiments.
- **Efficiency**: The speed and resource consumption of the model.
- **Scalability**: The model's performance when applied to large datasets.

This thesis will compare various algorithms, including Naive Bayes, SVM, and ensemble methods, to determine their effectiveness in sentiment analysis.

Research Goals

The primary goals of this research are to:

- Assess the current state of machine learning algorithms in sentiment analysis.
- Identify potential improvements and innovations in the field.
- Provide a comprehensive analysis that can guide future research and practical applications in sentiment analysis.

REVIEW OF LITERATURE

Dictionary is utilized to get the extremity of words through assessment for the area of news and web journals. Programmed manufacturer of dictionary based co-event of words is created and reached out to discover the absence of co-event. Path et.al., (2012) use machine learning for media investigation to find archives with positive and negative idealness. Order the audits dependent on quality, for example, high, medium, low, copy level and spam utilizing Support Vector Machine. Zhang et.al., (2011) utilize Naive Bayes and Support Vector Machine to characterize Cantonese surveys (language of Southern China) as positive and negative. The result shows that Naive Bayes performs better than Support Vector Machine for this situation. The current senti-dictionary needs giving space to assessment words since positive arrangement exactness is 10% higher than negative which diminishes normal precision. Upgraded Naive Bayes is utilized for eatery survey set to tackle the issue. Regularly individuals are searching for electrifying news from news stories. In this way every magazines and dailies have rivalry not exclusively to fulfill the perusers yet in addition increment their deals by giving thrilling news. Schumaker et.al., (2012) estimate the value changes which are identified with extremity of news stories.

METHODOLOGY

The rapid increase in mobile device usage has popularized academic strategies such as Mobile Learning (M-Learning). Various M-Learning systems are available, and user opinions about them are widely distributed across social blogs and review sites. Analyzing and categorizing these reviews as positive, negative, or neutral can be tedious. Opinion mining, the latest research area, analyzes users' opinions about products/services to help companies improve quality and gain insights into customer assessments.

Data Collection

The data for this study was collected from students' feedback on M-Learning systems available in the Android market. Reviews were gathered using data retrieval technologies to obtain sentiment data on M-Learning systems.

METHODOLOGY

1. **Data Preprocessing:**
   - Collect and clean the data by removing irrelevant information such as HTML tags, special characters, and stop words.
   - Tokenize the text into meaningful words or phrases.

2. **Feature Extraction:**
   - Extract relevant features from the text using Natural Language Processing (NLP) techniques.
   - Identify sentiment-related words and phrases that indicate positive, negative, or neutral opinions.
3. **Sentiment Analysis:**
   - Apply machine learning algorithms to classify the sentiment of the reviews.
   - Use supervised learning methods with labeled datasets for training the sentiment analysis model.
4. **Genetic Optimization:**
   - Implement a genetic optimization approach to enhance the performance of neural network-based algorithms.
   - Optimize parameters such as learning rate and momentum to achieve better classification accuracy.
5. **Evaluation:**
   - Assess the performance of the sentiment analysis model using accuracy, precision, recall, and F1-score.
   - Compare the optimized model with standard models to demonstrate the improvement in classification accuracy.

Tools and Technologies

- **Natural Language Processing (NLP):** For text processing and feature extraction.
- **Machine Learning Algorithms:** For sentiment classification.
- **Genetic Optimization Techniques:** To enhance the accuracy of neural network-based algorithms.
- **Data Retrieval Technologies:** For collecting user reviews from online sources.

This methodology outlines an approach to enhance M-Learning systems by analyzing user opinions, providing insights that can be used to improve the effectiveness and user satisfaction of M-Learning platforms.

Architecture of GKINN

The proposed GKINN Genetic (named after the research guide Dr. KIrubakaran and the researcher Prof. Nisha Jebaseeli) Neural algorithm, consists of two enhancements over the existing FFNN.

- Applying Crossover and Mutation on the population
- Genetic optimization of the learning rate and momentum.

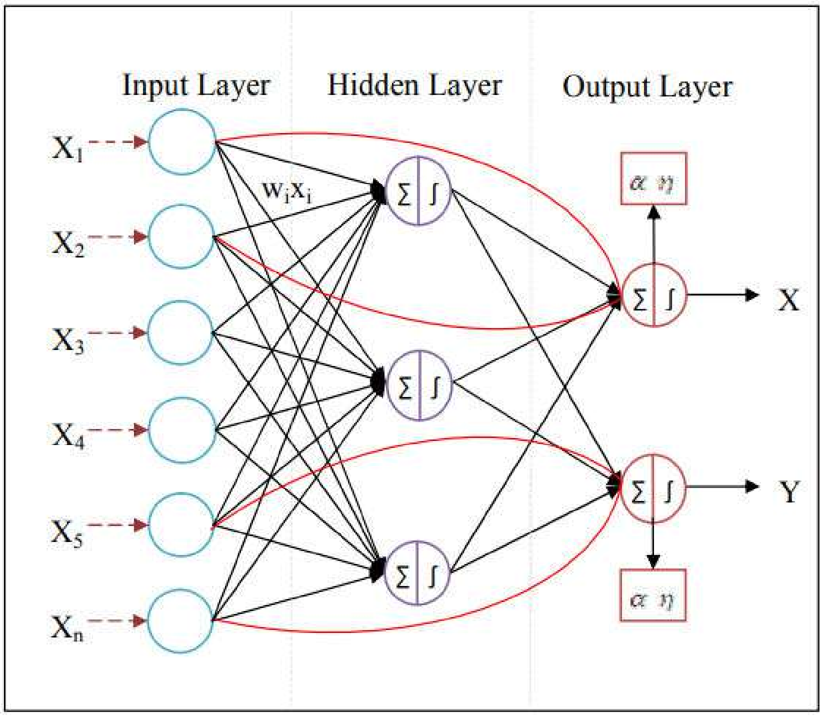

Figure 1: Architecture of GKINN

RESULT AND DISCUSSION

We gained the Amazon dataset from the Kaggle site of CSV designs and marked dataset. As Amazon audits come in 1-star to a 5-star rating and the 3-star evaluations is considered as nonpartisan surveys meaning neither positive nor negative. Information will be introduced in an organized manner, and there is no equivocalness in the information. The recovered information might be put away in a record, printed, or saw on the screen. In light of our framework necessity dataset are gathered as a portion of the datasets will be the tremendous size which we need to break down those before utilizing it.

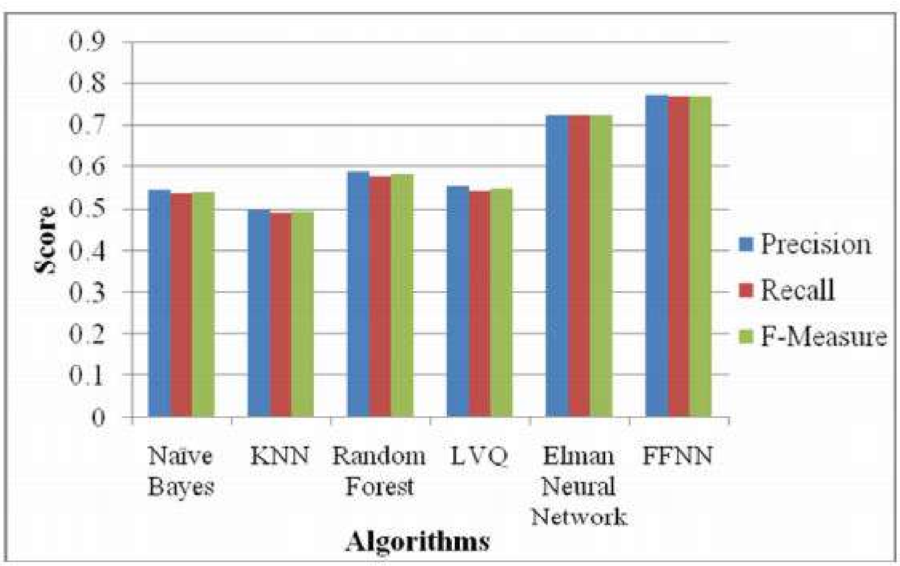

Figure 2: Precision, Recall and F-Measure without KN Preprocessing

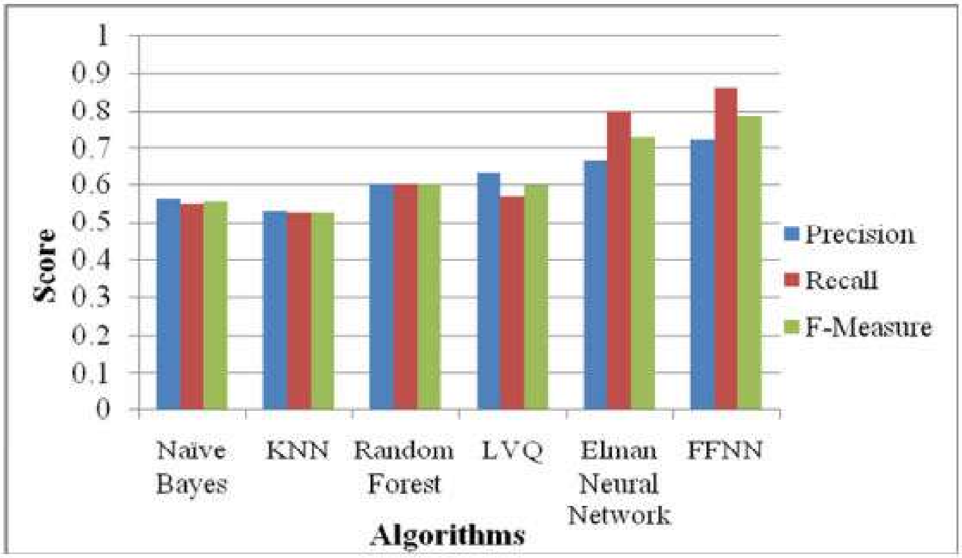

Figure 3: Precision, Recall and F-Measure with KN Preprocessing

From the analysis, the proposed KN preprocessing algorithm improves the classification accuracy. The exhibition of the machine learning calculation is assessed utilizing Precision, Recall and F-Measure. Exactness is the division of recovered cases that are significant and review is the portion of applicable cases that are recovered. F-Measure is the Harmonic mean of Precision and Recall. Exactness and review are the opposite relationship, where it is conceivable to expand one at the expense of diminishing the other. The results of the classifiers are spoken to as disarray framework or possibility table. The disarray grid has four classifications as appeared in Table 4.6. Genuine Positives (TP) are cases accurately named as positives. Bogus Positives (FP) allude to negative occasions mistakenly named as positive. Genuine Negatives (TN) relate to negatives accurately marked as negative. At last, False Negatives (FN) alludes to positive models inaccurately marked as negative.

Table 1: Confusion Matrix labels

Label	**Actual class**	
Predicted Class	True Positive	False Positive
	False Negative	True Negative

The proposed KINN algorithm is operated with M-Learning system reviews as dataset. Learner's opinions about free M -Learning system available are considered. The preprocessed dataset using KN preprocessing algorithm is applied in KINN algorithm for classification. The classification accuracy obtained from the experiment reaches up to 83.33%. The experiment with the acquired dataset has revealed that the increase of classification accuracy. The same algorithm is also commendable when the existing datasets are used. In the later, the evaluation of the algorithm with existing datasets is provided.

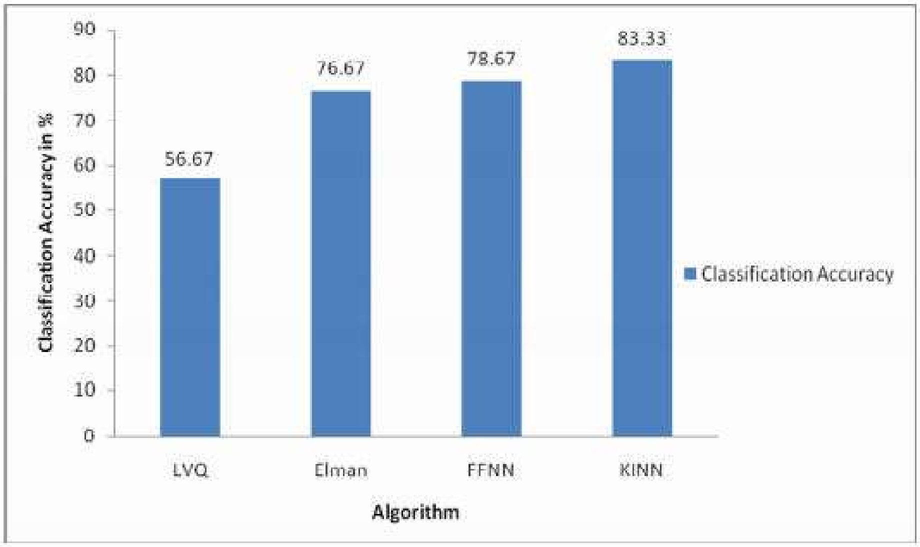

Figure 4: Comparison of KINN with Existing Algorithms

The got grouping exactness from the classifiers is approved utilizing Precision, Recall and F-Measure. Accuracy is the likelihood that the recovered record is important and Recall is the likelihood that a pertinent archive is recovered in an inquiry. F-Measure is the consonant mean of Precision and Recall. The Validated measures are appeared in Table 2, for the FFNN and the proposed KINN classifiers.

Table 2: Precision, Recall and F-measure of M-Learning Dataset

Algorithms	Precision	Recall	F Measure
	M Learning Dataset		
FFNN	0.667	0.8	0.727
KINN	0.837	0.826	0.831

Thus the proposed algorithm is validated against the existing ANN classifiers with Precision, Recall and F-Measures.

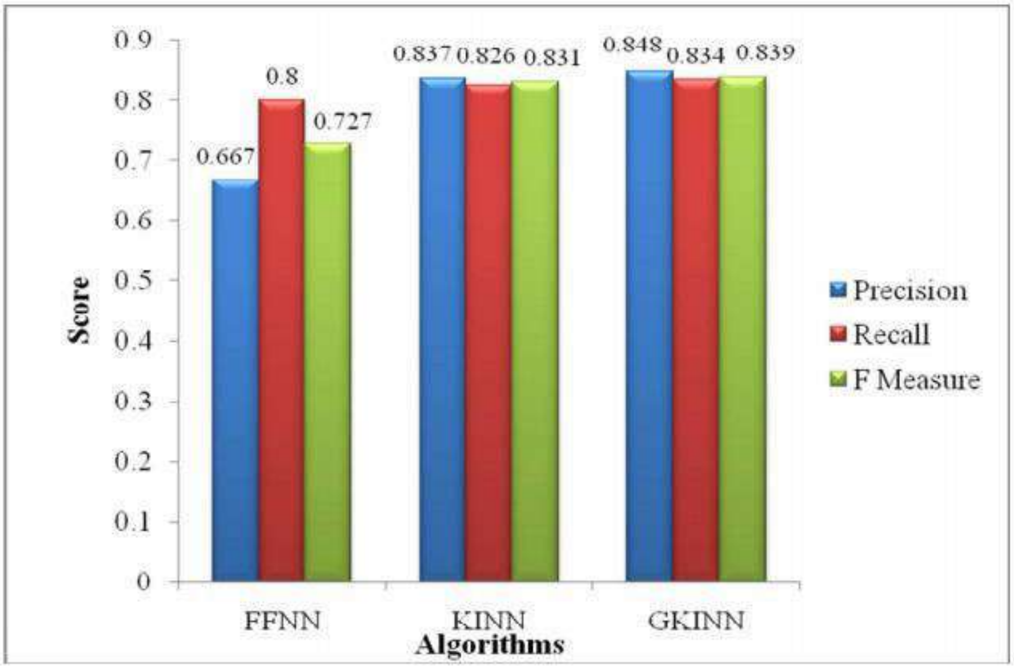

Figure 5: Precision, Recall and F-measure of M-Learning Dataset

Thus, the proposed algorithm is validated against the ANN algorithms with Precision, Recall and F-Measures.

CONCLUSION

This study demonstrates the effectiveness of AI-driven machine learning algorithms in sentiment analysis, with a particular focus on opinion extraction from online content. By comparing traditional data mining classifiers with neural network classifiers, we identified the superior performance of the KINN algorithm, which incorporates genetic optimization techniques. Our experimental results, based on data from Kaggle and student feedback on M-Learning systems, show that the KINN algorithm significantly enhances classification accuracy, achieving up to 83.33%. The findings suggest that integrating sophisticated algorithms like KINN can lead to more precise sentiment analysis, providing valuable insights for businesses and researchers. Future research could further explore the application of these techniques to larger and more diverse datasets, as well as the integration of additional contextual and semantic analysis methods to refine sentiment classification further.

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