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An optimized hybrid web-based system for sentiment analysis using machine learning

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Abstract

By including visual materials into the study, present work fills in the void in conventional sentiment analysis, which mostly depends on textual data. To find emotional insights from photos, the new method integrates sentiment analysis, semantic web technologies, and sophisticated image processing methods. Deep learning models help to gather visual data including objects, colors, and facial expressions using deep learning models. Then, using ontologies, these characteristics are linked to semantic concepts to create a knowledge network allowing logical process-based emotional deduction. The main discovery is that, especially in context-aware sentiment categorization, our CNN-RESET hybrid strategy beats conventional techniques. This integration of unstructured image data with structured semantic frameworks offers a deeper, more comprehensive understanding, with applications in social media monitoring, advertising, and human-computer interaction.

Subject Classification: *68U10, 68T45, 68T10.*

Keywords: *Sentiment analysis, Textual data, Semantic web technologies, Deep learning, Context-aware sentiment classification.*

This article has been corrected with minor changes. These changes do not impact the academic content of the article.

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1. Introduction

The use of a hybrid model that mixes a method based on vocabulary, deep training (DL) and machine learning (ML) has a significantly developed analysis of the atmosphere, an important component of natural language processing (NLP) [1]. Using the advantages of each individual approach, these hybrid strategies improve performance. For example, hybrid tools and methodologies were thoroughly studied to determine their functions in the mood analysis task [1]. Gandhe et al. [2], you can csombine mood analysis and adaptive profile ring to improve advisory applications. In order to increase the relevance of accuracy and situation, the classification of hybrid emotions on Twitter was irradiated using analysis based on the side [3].

The hybrid model was also applied to multilingual contexts such as the mood analysis of the social network of Indonesian language [4]. Success and problems in the development of these hybrid approaches are well recorded [5], and homogeneous ensemble classification was also used to increase the result of mood classification [6]. The classification of tweets based on semantic and frequency hybrid classifiers has shown significant improvements in the atmosphere detection [7], and hybrid methods based on filters and evolution rappers effectively consider the analysis of the subject emotions on Twitter [8].

Transition learning was used to classify the atmosphere based on the side of the application of the application, such as the side detection of the drug reaction, using a model such as XLNET [9]. The approach to hybrid text, the combination of content analysis, the mood analysis based on ML, and the analysis of the co -layer were also used to evaluate the atmosphere of the public in relation to the designated academic issues such as North Korea [10]. In the same area as a film review, the hybrid twin 2-regulatory RNN provided reliable performance [11].

During the covid-19 pandemic, the atmosphere analysis has been transferred with the DL Hybrid model, and the online review analyzes the open atmosphere, and the frame such as DT-FNN provides an effective classification of the Twitter atmosphere [13]. In the machine learning situation, a hybrid algorithm approach was also studied for comparative analysis of the mood [14]. Research in the field of electronic training is beneficial in adaptive profiling with mood analysis [15].

The reliability assessment of the Arab medical page was considered using ML of hybrid approaches [16]. Similarly, with the regression of the logistics, the syntax on the vocabulary -based function improved the mood analysis based on the side [17]. The analysis of product review using hybrid approach to deep training has also improved performance indicators [18]. The hybrid deep learning model was developed to handle the ensemble atmosphere on the e-commerce and S-commerce platform [19]. The atmosphere analysis based on the side of the social multimedia content using a hybrid computing frame has gained popularity [20] and was effectively used to place LSTM with the news of the news [21]. The adaptability of electronic training has increased by using a hybrid deep learning model that automatically identifies style and training [22]. In the field of library science, hybrid ML and vocabulary approaches found a mood model in the user review [23].

In the recommended system, the hybrid deep learning model and the mood analysis are integrated to increase accuracy [24]. The optimization method, such as the elephant optimization (EHO), combined with the hybrid DL to analyze the atmosphere of the online catering service on Twitter [25]. In addition, hybrid classifiers using CNN and Fuzzy C4.5 in the Hadoop-based infrastructure showed extension and accuracy in tweet analysis associated with Covid-19 [26]. We studied the innovative hybrid framework of AI based on the establishment and optimization of words and optimization to analyze the review of applications and mobile phones. In addition to traditional applications, ML played a decisive role in a system that confirmed the identification of cryptocurrency transactions without a key [28], and recognized the expressions of a person who used fusion at the sign level [29], and in real time autonomous trading system [30]. In addition, the classification of the data atmosphere of Twitter related to the renewable energy source using ML showed the importance of the hybrid model associated with the domain [31]. Hybrid atmosphere analysis continues to expand through various areas, providing reliable, expandable, and intellectual systems to understand complex human emotions and decision -making models. When this region moves, next -generation applications form more forms based on the merger and vision of NLP, ML, DL, and Semantic Web Technologies.

2. Literature Review

Present section presents existing research related to relevant area. Reviewing many hybrid tools and methods for sentiment analysis, Ahmad et al. [1] underlined the benefits of aggregating several approaches to improve accuracy and performance. Mostly driven at enhancing recommender applications, Gandhe et al. [2] presented a hybrid learning model for sentiment analysis of Twitter data. Emphasizing Twitter aspect-based sentiment analysis, Zainuddin et al. [3] presented a hybrid sentiment classification model. Developing a hybrid model for Indonesian social media sentiment analysis, Putra et al. [4] combined ML and rule-based approach. Appel et al. [5] investigated achievements and difficulties of creating hybrid method of sentiment analysis. Combining homogeneous ensemble classifier, Handhika et al. [6] presented a hybrid sentiment analysis. Menaria et al. [7] suggested a hybrid sentiment categorization method including frequency-based and semantic aspects. Approach maintained good classification performance across many subjects while efficiently lowering feature dimensionality [8]. Using a hybrid ontology-XLNet transfer learning for sentence-level aspect-based sentiment analysis in detecting ADRs, Sweidan et al. [9] presented using a hybrid text mining technique, Park et al. [10] investigated the impact of entertainment on popular opinions about North Korea. For movie review sentiment analysis, Soubraylu [11] used hybrid convolutional bidirectional RNN model. Applying DL-based sentiment analysis to COVID-19 public evaluations, Mengistie [12] showed how hybrid DL might be successfully used to evaluate public opinions during a global crisis. For Twitter sentiment analysis, Naz et al. [13] presented a hybrid classification system grounded on DT-FNN. For sentiment analysis, Singh et al. [14] compared many hybrid ML. Combining sentiment analysis with adaptive profiling, Ezaldeen et al. [15] put forth a hybrid e-learning advice. To evaluate the authenticity of Arabic medical online content, Alasmari et al. [16] used hybrid ML. For aspect-based sentiment analysis, Kabir et al. [17] presented hybrid syntax dependency model including Lexicon and logistic regression. Kuang et al. [18] created a hybrid DL for sentiment analysis in product evaluations. Ensembled sentiment analysis in e-commerce and s-commerce platforms, Venkatesan [19] put out a fresh hybrid deep learning model. For social multimedia's aspect-based sentiment analysis, Rana et al. [20] created hybrid computational architecture.

3. System Architecture

Combining several machine learning techniques in the proposed hybrid web-based sentiment analysis system helps to increase sentiment categorization accuracy and efficiency. System is built as a scalable, web-based platform able to analyze real-time textual data from multiple sources. Among other levels, data gathering, preprocessing, feature extraction, model training, sentiment categorization, web-based visualization formulates the architecture.

3.1 *System Components*

There are four main architectural components:

- **Data Acquisition Layer:** Data is gathered assuring continual and real-time data harvesting via APIs, web scraping, or database connections.
- **Data Preprocessing Layer:** This layer implements required preprocessing steps to improve the input text quality.
- **Feature Extraction Layer:** By use of many feature extraction approaches, this layer turns textual input into numerical representations.
- **ML Layer:** System's fundamental idea is a hybrid method using many ML models to improve sentiment categorisation accuracy by means of combination.
- **Sentiment Classification Layer:** After model analyses input text, system assigns emotions into predetermined categories.

3.2 *System Workflow*

The method of operation of the system guarantees effective sentiment analysis by means of a disciplined pipeline. Data is first gathered from many sources and cleaned and ready for study by means of preprocessing.

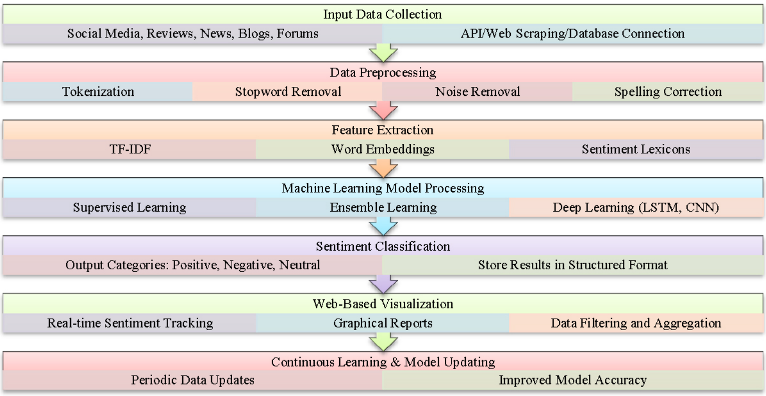

Figure 1

The system architecture of CNN-RESNET model

Feature extraction turns the text into a machine-readable format; machine learning models identify sentiment. Online visualisations then help to convey and analyse the data. Models are updated frequently utilising fresh data by means of constant learning, therefore guaranteeing better accuracy over time.

3.3 *Technologies Used*

The proposed approach takes use of many technologies. Programming languages like Python and JavaScript are included with machine learning frameworks. In web development React.js runs the frontend; Flask or Django is used for the backend. MySQL and MongoDB govern database operations while cloud services as AWS or GCP provide scalable storage and deployment capacity. System design might provide a great platform for an ideal hybrid web-based sentiment analysis system. Using interactive visualisation, real-time data processing, and advanced machine learning techniques as well as by means of their recommended design, sentiment classification accuracy and usability are aimed to be improved. Future developments might involve integration of multimodal sentiment analysis and improved model adaption to shifting speech patterns.

4. Proposed Hybrid CNN-RESNET model

Designed to take use of CNN's capabilities as well as ResNet's, hybrid CNN-ResNet model seeks stronger feature extraction, better gradient flow, and higher classification accuracy. It starts with a CNN-based feature extractor to collect low-level spatial information, model proceeds. This is accomplished by means of a sequence of convolutional and max-pooling layers, therefore enabling the model to learn hierarchical representations gradually. Following first feature extraction, the obtained features are fed into a ResNet backbone, more especially, ResNet-50 trained on ImageNet. ResNet offers skip connections, which allow deeper networks to train efficiently and assist to reduce vanishing gradient issue. This guarantees preservation of low-level as well as high-level characteristics, hence strengthening the feature representation. Originally supposed to be non-trainable, the ResNet backbone is meant to use its pretrained information while concentrating training on recently added layers. Following the ResNet layers, the retrieved features are flattened and fed via a fully connected (dense) network, hence improving the learnt representations. This model delivers greater accuracy, lower computational inefficiencies, and better learning stability by integrating CNN's strong spatial feature extracting skills with ResNet's capacity to effectively manage deep networks. The simulation parameters stated in Table 2 specify the key configurations and settings used for building and evaluating the ideal hybrid web-based sentiment analysis system.

Table 2

Simulation Parameters for this system

Parameter	Value/Description
Language	Python, JavaScript
Frameworks Used	Flask/Django (Backend), React.js (Frontend)
ML Models	SVM, RF, NB, LSTM, CNN, Ensemble Learning
Feature Extraction	TF-IDF, Word2Vec, GloVe, BERT, Sentiment Lexicon
Dataset Sources	Social Media, Product Reviews, Blogs, News, Forums
Preprocessing Techniques	Tokenization, Stopword Removal, Stemming, Lemmatization, Noise Removal
Training Data Size	Variable
Testing Data Size	20% of the total dataset
Performance	Accuracy, Precision, Recall, F1-score
Visualization Tools	Matplotlib, Seaborn, Plotly, Dash
Database Used	MySQL, MongoDB
Cloud Integration	AWS, Google Cloud Platform (Optional)
Hardware Configuration	16GB RAM, GPU (NVIDIA RTX 3060), 1TB SSD
Operating System	Windows 10/11, Linux (Ubuntu 20.04)
Simulation Software	Google Colab, Jupyter Notebook, Anaconda

Block Diagram Components

1. **Input Layer:** Accepts image data (e.g., 224 × 224 × 3 for RGB images).
2. **CNN Feature Extraction Block**
   - Convolutional Layers: Extracts low-level features like edges, textures.
   - Max-Pooling Layers: Reduces spatial dimensions and preserves important features.

3. **ResNet Backbone (Feature):** Pretrained ResNet50 Model and uses skip connections to maintain gradient flow and enable deeper learning.
4. **Fully Connected Layers**
   - Flatten Layer: Converts extracted features into a 1D vector.
   - Dense Layers: Performs classification using ReLU activation.
   - Dropout Layer: Prevents overfitting.
5. **Output Layer:** Uses Softmax activation for multi-class classification.

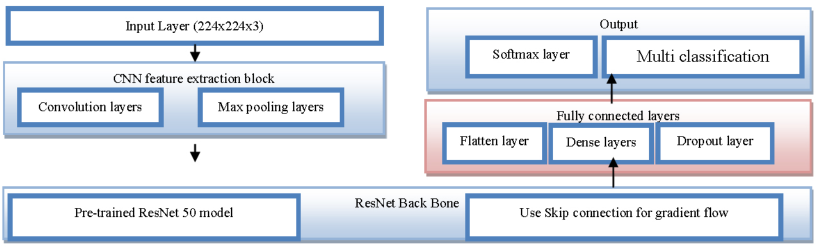

Figure 2

Layered Architecture of Proposed CNN-RESNET Hybrid model

Algorithm for CNN-RESNET Hybrid Model

1. Input two data sets LFW and CPLFW of Facial images
2. Apply compression on the image
3. Apply Gaussian filter on compressed image for noise removal and segmentation
4. Split images for training and testing in ratios 80:20 and 70:30.
5. Initialize Hyperparameters
   a. Batch size=16
   b. Learning rate = 0.01
   c. Optimizer = ADAM, SGD
   d. Epoch e
6. Initialize CNN Model
7. Initialize Resnet Model
8. Integrate ResNet and CNN and define Hybrid Model
9. Set i=1
10. Output: 'Hybrid: CNN-based sentiment analysis
    a. Auto_Enc: The learned AutoEncoder model
    b. for all $T_i \in X_{train}$ do

c. $Log \leftarrow getLogs(T_i)$
d. $RR_i \leftarrow extract\_gen\_feature(Log)$
e. $RR \leftarrow RR \cup RR_i$
f. end for
g. $(S_{train}, \theta_{train}) \leftarrow RR$
h. $Auto\_Enc \leftarrow TrainAutoEncoder(S_{train}, \theta_{train})$
i. $RR_e \leftarrow Embedding(Auto\_Enc, RR)$
j. $Hybrid \leftarrow TrainModel(RR_e)$
k. Consider Hybrida as a trained model for ADAM and Hybridb for SGD

11. Find the training and testing time of ADAM and SGD, and compare them on both datasets
12. Find Accuracy parameters using equation (1)-(4)
13. Find Sensitivity and Specificity using equation (5)-(6)
14. Compare all these accuracy parameters to conventional CNN models

5. Experiments and Evaluation

By combining image processing techniques with semantic web technologies, our proposed strategy offers a complete, context-aware way of sentiment analysis. By integrating semantic information from ontologies and linked data, the research shows how well the model performs above standard sentiment analysis approaches, hence improving accuracy.

5.1 *Dataset*

To ensure our studies were exhaustive and varied, we used sentiment analysis and image processing on many publically available datasets. To create an image dataset, we gathered a wide spectrum of images and tagged them with positive, negative, and neutral emotions. Source of dataset is https://kaggle.com.

Preprocessing:

- Image Resizing: Images are reduced to a constant dimension to guarantee that DL model's input size is uniform. Eliminating discrepancies assures that CNN input images are consistent in size.
- Normalization: The input data is normalised to a range of [0, 1] so that models are not distorted by variations in pixel intensities.

- Augmentation: Techniques help to improve the photos thus strengthening the model and ensuring its ability to properly handle fresh, unknown images.

Textual Data Processing: It consists of tokenising pertinent textual data. It is pre-processing before merging the textual data with the image features for sentiment analysis.

5.2 *Method Evaluation*

The performance of the proposed system was evaluated using many extensively used metrics in sentiment prediction. Accuracy counts precisely identified instances from the dataset. The percentage of precisely expected happy emotions to the whole range of positive emotions is one indication of accuracy. Recall, which is defined as the percentage of positive emotions that were precisely projected to entire good sensations, is crucial indicator of accuracy of model in spotting real positives. F1-Score, Especially in situations where distribution of classes is not homogeneous, this consistent metric considers both recall and accuracy, therefore providing a balanced view.

5.3 *Integration of semantic web with CNN-RESENT to develop hybrid model*

The combination of semantic web technologies and CNNs represents a powerful synergy that enhances the accuracy and depth of sentiment analysis in images. CNNs, widely regarded for their proficiency in feature extraction from images, primarily focus on identifying visual features like faces, objects, and color schemes. However, while CNNs excel at detecting low- and mid-level features from raw pixel data, they often struggle to understand the context of these features and their emotional significance. This is where semantic web technologies step in to enhance the overall performance.

6. Results and Discussion

The suggested sentiment analysis method is a considerable advance over other approaches; it integrates semantic web technologies with image processing. The system's accuracy parameters are improved with the use of contextual knowledge via semantic reasoning and mapping. However, in order to fully optimise its practical use, issues such as visual ambiguity, ontology constraints, and scalability must be resolved. Improving reasoning processes, incorporating current ontologies, and testing the system on huge datasets are all areas that might be explored further to enhance its flexibility and robustness. Present research is using python code to implement conventional CNN and hybrid CNN model with integration of semantic web over google colaboratory.

6.1 *Analysis of Results*

Hybrid model has simulated system's performance to training and testing accuracy at different epoch.

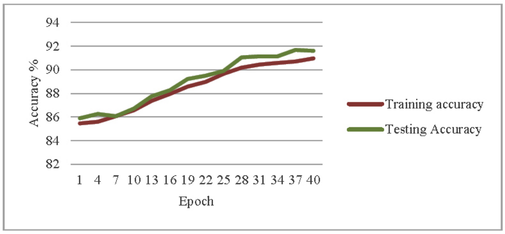

Figure 2

Epoch wise training and testing accuracy in case of hybrid model

The training and testing loss has been shown in following figure

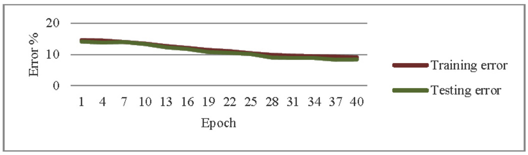

Figure 3

Epoch wise training and testing loss in case of hybrid model

Hybrid system that is considering CNN-RESNET based deep learning for sentiment analysis has been compared to conventional in table 3:

Table 3

Comparison of Traditional vs. Proposed System (With Semantic Web Integration)

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Ahmad et al. (2017) [1]	85.2	83.5	84.1	83.8
Zainuddin et al. (2018) [3]	89.4	88.1	88.9	88.5
Ezaldeen et al. (2022) [15]	91.5	90.3	90.8	90.5
Proposed System	93.2	91.8	92.4	92.1

In comparison to the standard approach to image-based sentiment analysis, suggested system consistently outperforms it. The following bar charts illustrate the two methods used to graphically represent these increases:

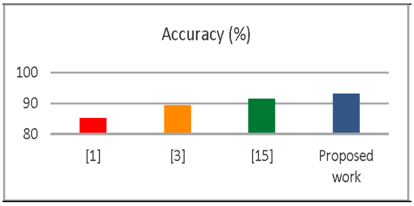

Figure 4
Comparison of Accuracy

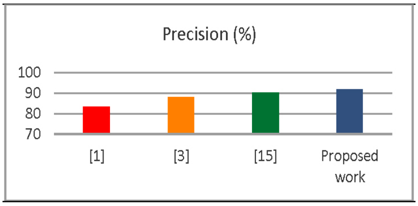

Figure 5
Precision Comparison

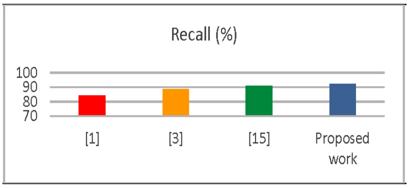

Figure 6
Recall Comparison

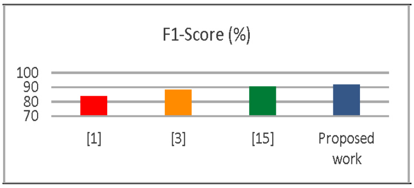

Figure 7
F1-Score Comparison

6.2 *Challenges and Limitations*

Although using the recommended strategy shows some positive results, merging sentiment analysis with the semantic web has resulted in several restrictions. Image ambiguity presents a challenge for sentiment classification as it makes things more complex.

6.3 *Real-World Applications*

The proposed approach offers various feasible real-world uses in several different sectors. Social media sentiment analysis first allows one to monitor current mood by means of images posted by others and thereby ascertain their opinions.

7. Conclusion

In this work, we proposed a novel method for sentiment analysis combining image processing methods with semantic web technologies. The main output of this work is a hybrid system combining semantic reasoning grounded on ontologies and knowledge graphs with conventional image-based sentiment analysis. Proposed work is yielding better accuracy, precision, recall, and F1-score as compared to conventional models.

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