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Novel heuristic-based hybrid ResNeXt with recurrent neural network to handle multi class classification of sentiment analysis

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Abstract

Present-day, interdisciplinary research is increasing in social network-related applications, and it is a daily routine activity in every human life. So, sentiment analysis (SA) based on opinion mining is the most sophisticated concept in the well-known social network environment. Different machine learning methods were implemented to extract different text label features in SA, and all of those methods can detect whether a given text is positive or negative based on the text features. Analysis of sentiment has been suffering from inaccuracies while using machine learning and sentiment-based lexical methods dependent on domain-specific problems. Multi-class SA is an expensive task where memory, label samples, and other parameters are insufficient. So, we propose and implement a novel hybrid model which is a combination of ResNeXt and recurrent neural framework (NH-ResNeXt-RNF) to explore multi-class sentiment from textual features. This framework investigates the polarity of words connected to a specific domain across the entire dataset and eliminates noisy data in an unsupervised manner using pre-processing. Optimization is required to perform efficient multi-class classification to reduce the effort associated with annotation for multi-class SA via unsupervised learning. The proposed model performance is evaluated on two data sets namely: Amazon and Twitter. We increase the accuracy of the sentiment of polarity on each sentence present in the data set. Experimental results of the proposed approach give better and more efficient multi-class (**positive, negative, very positive, neutral and highly negative**) domain-specific sentiment than traditional approaches related to supervised, semi-supervised, and unsupervised domains. The proposed hybrid model accuracy is 96.5% and 95.37% for Amazon and Twitter datasets respectively.

1. Introduction

Every day, the social network is the new paradigm by which different humans share their professional and personal details among individuals or groups, and it has become an essential role in each human's daily lifestyle in a real-time environment [1]. The social network benefits users with advanced features offered by innovative communication environments to share data continuously. The problem with this communication is that the exchange of data performs different social network issues, with people primarily active on different platforms related to health, academics, education, and other related fields [2]. Improvements in the social network environment describe the analysis and constitute structure representation to explore the emotions of different human beings [3]. Sentiment analysis (SA), or mining of opinion, is a comprehensive problem in social networks to analyze feelings, opinions, ratings, and attitudes. Humans are categorized based on their emotions, product reviews, and individual personality assessments. Different social networking platforms produce enormous amounts of data. This data is beneficial to different organizations to evaluate and monitor the analysis of sentiment, product issues, etc [4–6]. Additionally, there are several forms of SA, including news comment analysis, product comment analysis, film comment analysis, and others. However, sentiment classification is a primary task in SA that seeks to detect sentiment polarities like positive and negative or to differentiate more fine-grained sentiment classes like extremely positive, positive, neutral, negative, and very negative [7]. In a real-time environment, different social networks are monitored by the organization to evaluate SA; as a result of SA, organizations have improved their activities in recent years [8]. Now, SA is being applied to all areas, including healthcare services, political events, and social activities. All these applications provide an efficient analysis of sentiment in practical research. Customer comments and micro blogs are two examples of large online articles that help estimate public sentiment. Whereas, different studies were introduced for SA or mining opinion with different supervised, unsupervised, and semi-supervised machine learning approaches. These machine learning techniques have been extensively used in sentiment categorization since the efficiency of machine learning is greatly relied on feature representation [9–11]. Many studies concentrate on building effective handcrafted features to build a potent sentiment classifier. Some of the machine learning-based classification approaches are support vector machine and naive Bayesian classifier. These algorithms are implemented to evaluate the sentiment of social network reviews and other issues [12]. In the field of text SA, building the sentiment lexicon has recently enabled several academics to combine deep learning and traditional machine learning approaches with promising results. However, deep learning techniques are often used in various industries, such as object detection, network optimization, image recognition, system security, sensor networks etc. On the other hand, if a high amount of labeled data is present, all these approaches fail to explore multi-class classification because of inaccuracies, the high amount of time-consuming and expensive implementation required for multi-labeled data [13, 14]. For domain-specific labeled data, some of the supervised learning approaches for classifying unseen objects, if there is any unlabeled content, then use semi-supervised learning approaches to classify labeled data [15].

So, we propose and implement a novel hybrid heuristic recurrent neural framework (NH-ResNeXt-RNF) to explore multi-class sentiment from textual features. This framework investigates the polarity of words connected to a specific domain across the entire dataset and eliminates noisy data in an unsupervised manner. We check the polarity of different words related to the sentiment with Intelligence-based optimization on evaluating specific words relating to very positive, very negative like 'great', 'excellent', 'fantastic', and 'awful', worst etc. The innovative features of the proposed approach are described as

1. A proper feature extraction procedure is incorporated to extract a relevant set of features which in turn reduces the feature dimension.
2. A novel hybrid heuristic recurrent neural network (NH-ResNeXt-RNF) is introduced to examine multi-classification sentimental tasks.
3. A hybrid black widow-moth flame optimization algorithm is proposed to tune the weight factors of the recurrent neural network (RNN) model, in turn, improve the classification task.

The rest of the manuscript is organized as follows; section 2 elaborates on related work. Section 3 discusses the research gap and further section 4 explains the proposed methodology. Results and discussion is offered in section 5. The final section 6 elaborates on the conclusion.

2. Related work

There exists generous examination of SA, and most dynamic exploration of the space accompanied by the blast of client-created content in online media, conversation discussions, sites, and audits. Since most investigations utilize or rely upon, machine learning (ML) drawing near; how many clients produced content gave limitless information to prepare. Some of the meta-heuristic calculations are discussed in the literature to implement novel applications developed for the scientific field. Some of the techniques are discussed in the classification of sentiment in bipolar classification i.e. positive, negative, and 3-label classification, which is positive, negative, and neutral. This writing survey outlines the various methodologies that can be applied for SA, just as brief clarifications of calculations utilized by analysts.

Existing techniques for semi-supervised multi-modality classification frequently optimize the multi-linear graph's relationship for label propagation. However, the linear fusion of multi-graph does not fully reveal the intrinsic manifold structure because of label variations in each iterating propagation. To assess how this nonlinear connection affects label propagation's classification performance, Lin *et al* [16] have presented dynamic graph fusion label propagation (DGFLP). This approach represents the diverse importance of multi-graph in the propagation process by taking into account both the relationship of multi-graph and the distinctive distribution of each graph. Likewise, Seng and Ang [17] have suggested a divide-and-conquer principal component analysis (Div-ConPCA) and the divide-and-conquer linear discriminant analysis (Div-ConLDA) for the extraction of multimodal data feature. This method incorporates five modules such as data collection, multimodal data feature extraction, multimodal data aggregation, fusion, decision module, at last, application module. On the other hand, Nemati *et al* [18] have

Table 1. Summary of literature review.

Authors (citations)	Year	Methodology	Challenges
Lin *et al* [16]	2017	Dynamic graph fusion label propagation (DGFLP)	This method requires further improvement.
Seng *et al* [17]	2019	Div-ConPCA-LDA	This method is not compatible with ever-growing emotion and sentiment databases.
Nemati *et al* [18]	2019	Hybrid fusion method	Further development is required for the textual modality's results.
Beigi *et al* [19]	2021	Sentiment classification model	Concept-level emotion adaption is not supported by this technique.
Fu *et al* [20]	2019	AL-SSVAE	This approach does not successfully anticipate the sentiment polarity of many aspects at once.
Xing *et al* [21]	2019	Cognitive-inspired domain adaptation	With a hierarchy of primitives, the methodology does not permit concept-level sentiment modification.
Akyol and Alatas [22]	2020	Sentiment classification within online social media using whale optimization algorithm	This method requires further improvement.

presented a hybrid multimodal data fusion approach. Here, a latent space linear map was employed to combine the audio and visual modalities. Then, projected characteristics were fused with the textual modality via Dempster–Shafer theory-based evidentiary fusion procedure. Then the findings of feature-level audio-visual fusion were obtained using the marginal Fisher analysis.

Beigi and Moattar [19] have presented a sentiment classification model. To eliminate the requirement for massive labeled datasets in an unsupervised way, this combination may concurrently adjust word polarities to the target domain and employ the polarity of the entire document. Furthermore, a domain-independent lexicon, consists of adjectives and static positive or negative ratings independent of a particular domain. Likewise, Fu *et al* [20] have implemented a Variational Auto encoder-based Semi-supervised Aspect Level Sentiment Classification Model for aspect-level sentiment classification. The AL-SSVAE model also features an aspect-level sentiment classifier and inputs a particular aspect to an encoder and decoder based on a variational Auto encoder. On the other hand, Xing *et al* [21] have presented a cognitive-inspired domain adaptation to train a basic emotion classifier while modifying word polarity for the intended domain. The polarity score of one word was updated while the search for fresh emotion words was balanced by an exploration-exploitation method. Additionally, Akyol and Alatas [22] have suggested a Whale Optimization Algorithm and Social Impact Theory-based Optimization Algorithm for the SA problem. Here, real IMDB and Amazon data sets were employed to estimate the suggested method performance. Similarly many approaches related to multi class sentiment classification [23–27] has been done in the previous studies but all those methods require better performance in terms of accuracy and the summary of literature review is presented in table 1 as shown below.

3. Research gap

The issues that various methodologies have, according to research done on the methods currently used to classify sentiments are as follows:

- The fundamental difficulty in classifying is the accuracy factor, which is impacted by the classifiers' use of nouns, adjectives, verbs, and other words rather than only taking into account the emotive terms in the evaluations. Additionally, the current approaches have mostly focused on phrase polarity rather than sentence form.
- Only the numerical rating and the word count of the review were used by certain categorization systems to gauge how well they worked. These methods ignored user numbers, unfavorable reviews, and both positive and negative reviews.

- The emotional analysis model has certain limitations due to overfitting and convergence within the bounds of optimization problems when utilizing conventional machine learning methods.
- The choice of the best characteristic that produces a better outcome is another problem with categorization systems. N-grams, words, syntactic n-grams of various sorts, or a mix of these characteristics, are among the features that can be chosen. Another issue that most of the current methods encounter is feature size.
- Online evaluations of user comments in the form of abbreviations, conjoined words, and shortenings, which are frequently used by individuals to communicate their thoughts about a certain subject, are one of the primary problems in emotional categorization. The current systems had polarity inconsistencies and were unable to cover all internet reviews.
- Because of its low computational complexity and slow convergence rate, current algorithms have difficulties. It has concerns with over-fitting, explosive gradients, and class imbalance which requires extra processing time.

The new approach known as NH-ResNeXt-RNF is designed to address these drawbacks and increase the convergence rate and to use the black widow optimization (BWO)-Moth flame optimization (MFO) method to develop a new classification model called NH-ResNeXt-RNF to maximize precision and accuracy. These difficulties lead the researchers to concentrate on creating a novel SA that takes product reviews into account.

4. Proposed methodology

Performing sentimental analysis task not only assist reference to other consumers but also increase service quality and consumer satisfaction on the e-commerce and social media platforms. Day by day, the demand for accuracy is playing a vital role in developing robust sentimental analysis systems. This research aims to develop a novel hybrid heuristic recurrent neural network model (NH-ResNeXt-RNF) to handle the multi-classification problem of sentimental analysis. The suggested NH-ResNeXt-RNF framework comprises distinct phases namely (a) pre-processing (b) feature Extraction (c) classification. The figure 1 demonstrates pre-processing of text for matured results.

White spaces and punctuation are used to tokenize reviews or tweets into words. Stop word removal, which removes meaningless words from the given feedback and punctuation removal, removes punctuation symbols (#, -, _,.,;:,, etc). Latin characters and digits removal cleans Latin and numerical data since they do not detect an input tweet's emotional classification. Diacritics removal, which involves removing diacritics like {,,,,,,,} since they are not used to extract and identify Arabic stems. Word normalization unites letters in distinct forms and light stemming removes prefixes and suffixes to simplify inflected words. To enhance the SA approach further the obtained input is passed to the feature extraction procedure.

Senti-WordNet is used to perform the feature extraction procedure on the pre-processed data to get the most relevant features while reducing the complexity. Finally, the classification model NH-ResNeXt-RNF is introduced which adopts a hybrid Recurrent Neural Network framework along with an optimization technique to perform the classification procedure. Further to improve the interpretability and generalization ability of the model, NH-ResNeXt-RNF incorporates a hybrid optimization technique to tune the design parameters of the classification technique.

4.1. Senti-WordNet-based feature extraction

In natural language processing (NLP), the method of extracting features aims to minimize the size of the features by converting pre-processed data into feature vectors. The main aim of reducing the feature size ensures the reliability of the system by encompassing a shorter text dataset. In the proposed methodology, the classification of sentimental analysis regarding product reviews relies on the Senti-WordNet-based feature extraction model. Senti-WordNet helps the classification algorithm to effectually classify reviews; meanwhile, it includes an opinion dictionary drawn from the WordNet repository. Before representing the features, let us indicate the database E and its corresponding fields. The pre-processed e-commerce database comprises $E = \{T_1, T_2, \ldots, T_o\}$; $1 \leqslant j \leqslant o$. Here the entire number of reviews in the database E is denoted as o. Here, reviews are presented as sentences that may be classified as either negative or positive. T_j comprehends set of words for the jth review which is represented as, $T_j = \{x_1, x_2, \ldots, x_n\}$; $1 \leqslant k \leqslant n$. Here the notation n indicates the number of words obtainable in the jth review. The feature vector of the jth review is represented as G_j which combines $G_j = \left\{g_j^1, g_j^2, \ldots, g_j^m, \ldots, g_j^{11}\right\}$, where g_j^m signifies the feature vector of mth feature. The words are divided into several synsets, or synonyms set, using SentiWordNet. Each synset has a score of polarity associated with it, such as the objective, negative and positive. For every synset, the scores range from 0 to 1, and their aggregate equals 1. It is feasible to determine if an opinion is objective, negative, or

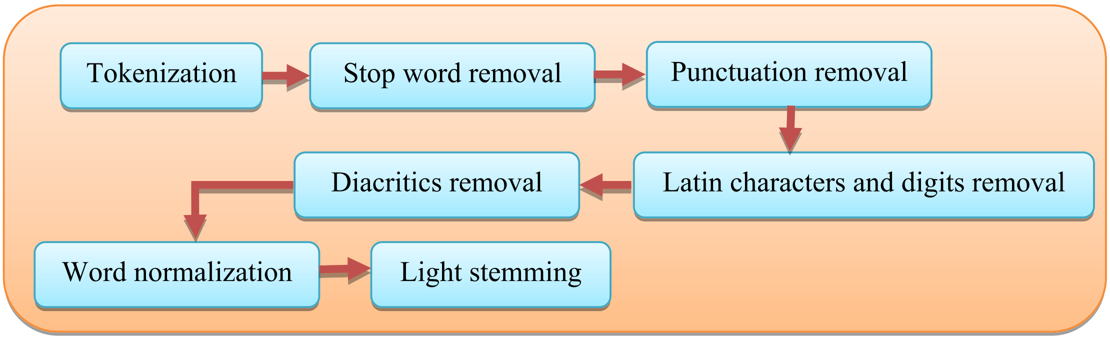

Figure 1. The review of pre-processing methodology.

positive dependent on the ratings given. Senti-WordNet uses software to assign scores to every word since the words in the database are dependent on the WordNet part of speech. The score values' weighting assessment can be seen as,

$$\left[\Phi^{j}(o), \Phi^{j}(n), \Phi^{j}(p)\right] = i\left(x_j\right). \tag{1}$$

In the Senti-WordNet model, the representation of objective, negative and positive scores is symbolized as $\Phi^{j}(o)$, $\Phi^{j}(n)$ and $\Phi^{j}(p)$ respectively. When the review carries the negative word, and then $\Phi^{j}(p) < \Phi^{j}(n)$ corresponds to $\left\{x^{N}\right\} \ll x_j$ is followed. In the same scenario, if the review carries positive words, then it achieves $\Phi^{j}(p) > \Phi^{j}(n)$ corresponds to $\left\{x^{P}\right\} \ll x_j$. When a term has a score of 0, it is considered to be objective because it is neither negative nor positive. Six more characteristics may be derived from the statistical data, as indicated below, based on the Senti-WordNet classification:

$$g^{1} = \frac{1}{|x^{P}|}\sum_{k=1}^{n}\Phi_{k}(p)\ \forall x_j \epsilon x^{P}. \tag{2}$$

Here is the positive score of kth word is indicated as $\Phi_{k}(p)$ whereas the positive word is denoted as x^{P}. The mathematical formulation of a negative score is calculated based on the following assessment,

$$g^{2} = \frac{1}{|x^{N}|}\sum_{k=1}^{n}\Phi_{k}(n)\ \forall x_j \epsilon x^{N}. \tag{3}$$

Similar to the above equation, the negative score of the kth word is indicated as $\Phi_{k}(n)$ whereas the negative word is denoted as x^{N}. The following two characteristics, g^{3} and g^{4}, depending on the frequency of positive and negative terms, making it simple to distinguish between favorable and unfavorable reviews:

$$g^{3} = \frac{1}{|x^{P}|}\sum_{k=1}^{n}\Phi_{k}(p) * g_k\ \forall x_j \epsilon x^{P} \tag{4}$$

$$g^{4} = \frac{1}{|x^{N}|}\sum_{k=1}^{n}\Phi_{k}(n) * g_k\ \forall x_j \epsilon x^{N}. \tag{5}$$

Here g_k indicates the frequency of positive and negative words contained in the review of kth word. Based on the variance functionality, further features are determined to identify whether the review fits negative or positive words. When calculating variance, g^{5} is regarded as the difference between a particular feature from the positive score and the positive word,

$$g^{5} = \frac{1}{|x^{P}|}\sqrt{\sum_{k=1}^{n}\left(g^{1} - \Phi_{k}(p)\right)^{2}\forall x_j \epsilon x^{P}}. \tag{6}$$

In the review, the positive score is symbolized as $\Phi_{k}(p)$ with the frequency of kth positive word. The variance between a negative score and a negative word is calculated using the statistical feature g^{6} which is mathematically expressed as,

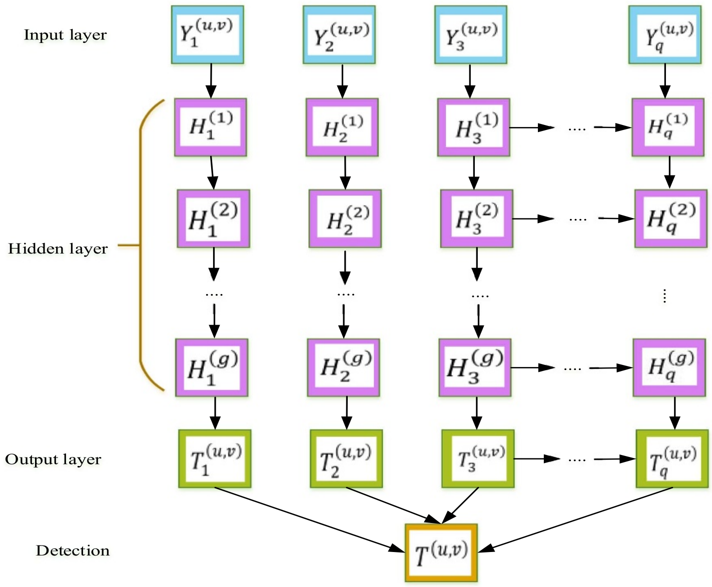

Figure 2. Architecture of the classification system.

$$g^6 = \frac{1}{|x^N|}\sqrt{\sum_{k=1}^{n}(g^2 - \Phi_k(n))^2}\ \forall x_j \epsilon x^N. \tag{7}$$

As a result, the review database is transformed into a feature vector of dimension 1×6 abbreviated as $[G_j]_{1\times 6}$. The obtained feature vector is subjected to the classification algorithm to perform the sentimental analysis task which is detailed in the following section.

4.2. Novel hybrid heuristic recurrent neural network

The RNN algorithm was chosen mostly for its ability to identify the sequential properties of the data and apply patterns to anticipate the following likely situation. The method incorporates layers, which provides the model with short-term memory and allows it to more accurately predict the following data while using memory. Nevertheless, incorrect parameter setup can result in non-convergence, high levels of unpredictability, and poor generalization. This paper suggests an novel hybrid heuristic (NHH) technique to address this problem, which boosts RNN parameters like batch size and weight functions while minimizing RNN drawbacks like unpredictability and instability. To categorize a multi-class emotional task, the generated feature vectors are processed through an NH-ResNeXt-RNF-based learning process. The weight values of the classifier are adjusted by a hybrid heuristic optimization approach to increase the effectiveness of traditional RNNs. Here, the extracted feature vector $[G_j]_{1\times 6}$ is fed into the ResNeXt, which uses weights, hidden layers, and bias functions to make a prediction. The classifier has numerous recurrent hidden layers and is organized as a network hierarchy. The suggested classification approach's recurrent link only appears between hidden regions. The input layer delegates its comparable result, provides it as the input to the following layer, and continues the iterative procedure using information from hidden layers. The most significant benefit of the proposed model over other deep learning classifiers is that it completes the classification process by having input characteristics of various lengths utilizing a series of data.

The figure 2 shows the basic cell of RNN with input, output layers and respective detection. The input layer of the suggested classifier is mostly carried by the following representation:

$$A^{(v,w)} = \left\{Z_1^{(v,w)}, Z_2^{(v,w)}, \ldots, Z_q^{(v,w)}, \ldots, Z_r^{(v,w)}\right\}. \tag{8}$$

In this case, the input layer of the vth the layer is identified at the wth period. The notation shown below represents the vth output layer at the wth time in a similar manner:

$$U^{(v,w)} = \left\{U_1^{(v,w)}, U_2^{(v,w)}, \ldots, U_q^{(v,w)}, \ldots, U_r^{(v,w)}\right\}. \tag{9}$$

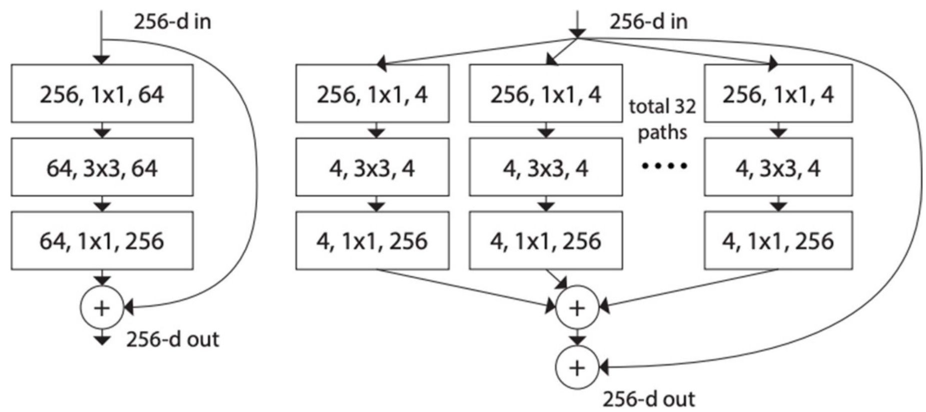

Figure 3. ResNeXt block.

Table 2. ResNeXt internal architecture.

Stage	Dimensionality	ResNeXt-50(32 × 4d)
Conv1	112 × 112	7 × 7, 64, stride 2
Conv2	56 × 56	3 × 3 max pool, stride 2
Conv3	28 × 28	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128, C = 32 \\ 1 \times 1, 256 \end{bmatrix} \times 3$
Conv4	14 × 14	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256, C = 32 \\ 1 \times 1, 512 \end{bmatrix} \times 4$
Conv5	7 × 7	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512, C = 32 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$
Conv1	112 × 112	$\begin{bmatrix} 1 \times 1, 1024 \\ 3 \times 3, 1024, C = 32 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$
Conv1	1 × 1	Global average pool 1000 d fc, softmax
	@params	25.0×10^6
	FLOPS	4.2×10^9

4.2.1. ResNeXt

Homogeneous neural network ResNeXt decreases ResNet's hyperparameters. They do this by adding 'cardinality' to ResNet's width and depth. Cardinality determines transformation size. The figure 3 shows the block of ResNeXt model.

The left component diagram in the above image is a traditional ResNet block, while the rightmost is the ResNeXt block, which has a cardinality of 32. The same transformations are applied 32 times, with the final result being aggregated.

4.2.2. ResNeXt architecture

ResNeXt's fundamental architecture is defined by two rules. First, if the blocks produce same-dimensional spatial maps, then they share the same set of hyper parameters, and if the spatial map is down sampled by a factor of 2, then the block width are multiplied by a factor of 2. The internal architecture of ResNeXt model is shown in table 2.

Figure 4; clearly demonstrate the hybrid model for SA which can use ResNeXt and RNN. The ResNeXt is very efficient model for extracting features and these features used for classification of sentiment using RNN cell.

In the two equations above, q stands for the vth layer arbitrary unit integer and r stand for the uth layer's overall number of units. Each set of input and output vectors has an element that is quantified in terms of unit. The arbitrary unit is denoted as r of the vth layer, whereas all the input and its corresponding output

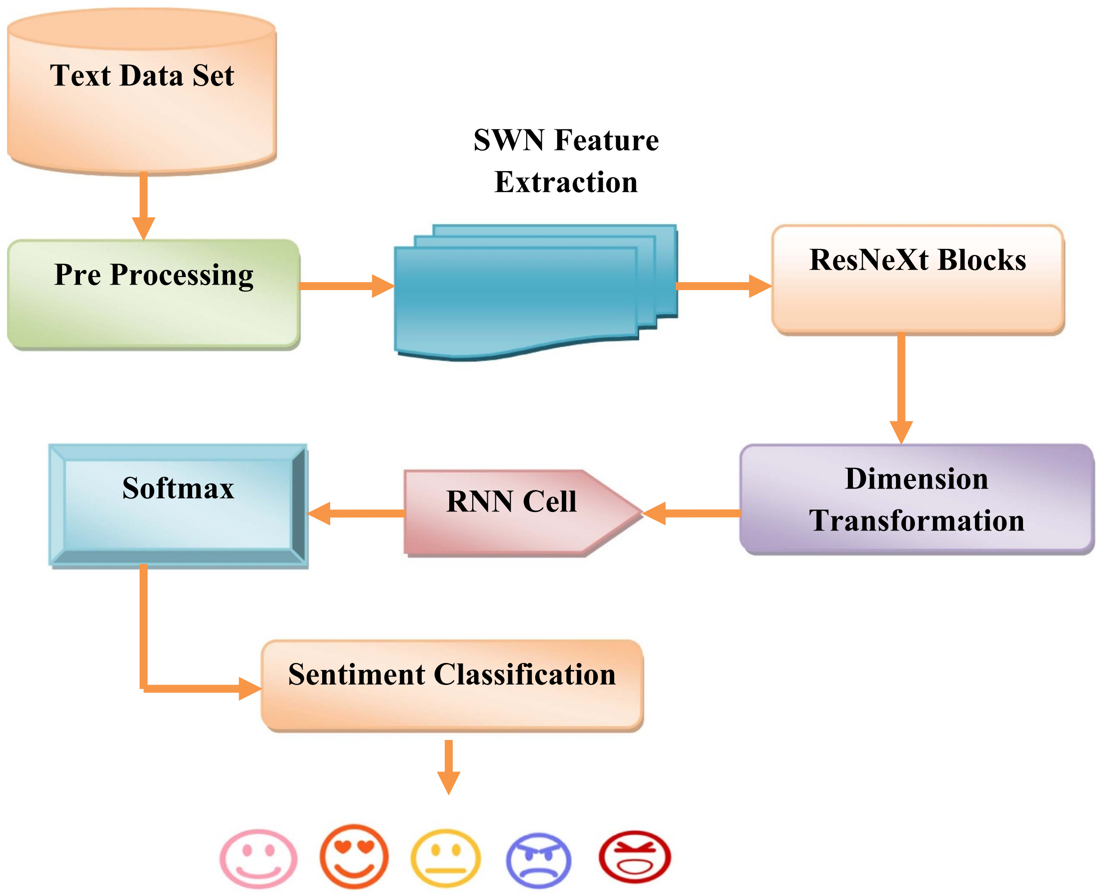

Figure 4. Proposed hybrid model (HR-ResNeXt-RNF) for sentiment analysis.

layer were indicated as a unit. The end layer is symbolized as $(v-1)$ th layer with its arbitrary layer. The recurrent weight factor of the vth the layer is represented as $Y^{(v)} \in C^{r\times V}$ while the weight factor of input propagation from the $(v-1)$ th layer to the vth the layer is marked as $y^{(v)} \in C^{r\times r}$. Here the term C represents the weight factor of its respective layer. The mathematical formulation of the input vector components is as follows:

$$Z_q^{(v,w)} = \sum_{i=1}^{V} w_{qi}^{(v)} U_i^{(v-1,w)} + \sum_{q'}^{r} \varepsilon_{qq'}^{(v)} U_{q'}^{(v,w-1)}. \tag{10}$$

The term $w_{qi}^{(v)}$ and $\varepsilon_{qq'}^{(v)}$ signifies the factor of $Y^{(v)}$ and $y^{(v)}$. The symbol for the arbitrary element's unit number in the vth layer is q'. The mathematical formulation for the output vector components of the v^{th} the layer is as follows:

$$U_q^{(v,w)} = \mu^{(v)} \left(Z_q^{(v,w)} \right). \tag{11}$$

The activation function is denoted as $\mu^{(v)}$. It may be seen as either a logistic sigmoid function or a sigmoid function. The two functions are denoted by the following formulas,

$$(Z) = \tanh(Z) \tag{12}$$

$$\mu(Z) = \frac{1}{(1+e^{-Z})}. \tag{13}$$

Additionally, the suggested recurrent feature set enhances classification performance in sentimental analysis. The weight value ith the term is converted to $w_{qi}^{(v)}$ to further simplify the classified method, and the unit of the term ith the function is indicated as $U_q^{(v-1,w)}$. The following equation resolves the bias term of the suggested deep learning architecture:

$$U^{(v,w)} = \mu^{(v)}.\left(Y^{(v)}U^{(v-1,w)} + y^{(v)}.U^{(v,w-1)}\right). \tag{14}$$

The output layer of the proposed system is denoted as $U^{(v,w)}$. Using a hybrid heuristic optimization strategy, the weight values of the proposed deep learning technology are customized in the best possible way. In turn, this enhances the performance of categorization. The proposed deep learning system utilizes the Moth flame and BWO algorithms as its training methods, which are referred to as hybrid heuristic optimization (NHH). Despite having superior searching capabilities, the traditional BWO approach has significant drawbacks, including slower search speeds and poor accuracy during the final iteration. By improving the update functionality of the moth flame optimization technique, this problem is resolved. An optimum collection of weight factors for each layer in an RNN may be generated using the suggested model. It should be noted that the efficacy of the recommended optimization technique has a high potential to accelerate the categorization process. The suggested optimization approach chooses and applies a weight factor to the RNN structure using these processes. To make the classification process simpler, the ideal weight factor is controlled as a solution vector at this point. This is calculated in terms of fitness function and may be accomplished by achieving the least error function. By performing a hybrid approach, the proposed optimization algorithm increases population variety to stop premature convergence and quicken convergence. The major focus of this part is on an NHH, where the hybridization of the Moth flame and BWO algorithms is covered in depth. In Moth flies, it can prevent early convergence by gradually increasing population variety. Additionally, it successfully supports the local optimum. In the section that follows, the mathematical representations of the initialization population, reproduction, cannibalism, mutation, and convergence. The flow chart of the BWO-MFO algorithm is shown in figure 5.

- **Initial population:** In the BWO algorithm, the male and female populations are required which are denoted as weight factors of the deep learning model, and the population is performed randomly. The initialization population of black widow spiders is depicted mathematically in the following.

$$X_{N,d} = \begin{bmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,3} \dots\dots x_{1,d} \\ x_{2,1} & x_{2,2} & \dots & x_{2,3} \dots\dots x_{2,d} \\ x_{N,1} & x_{N,2} & \dots. & x_{N,3} \dots\dots x_{N,d} \end{bmatrix}, lb \leqslant X_i \leqslant ub. \tag{15}$$

The population of the black widow spider is denoted by the notation $x_{N,d}$, where N stands for population size, d for the problem's number of choice variables, lb for the population's lower limit, and ub for its upper bound.

- **Fitness function:** The fitness value computation in this procedure is important; the fitness function is represented by the notation f at a widow. The fitness function of the suggested optimization method is calculated by comparing the classifier's actual and estimated result measures. The fitness value is used to determine the minimization function, which is then chosen as the best solution in the search space. The following determines how fitness function is represented mathematically:

$$f_n = \frac{1}{x}\sum_{e}^{x} T_e^{(u,v)} - \delta_e. \tag{16}$$

The fitness value for the nth atom is calculated using the equation above, and it is represented as f_n. $T_e^{(u,v)}$ the term denotes the actual output of the classifier, whereas δ_e defines the estimated output of the classifier. The categorization model's error functionality is indicated by the symbol e.

- **Procreate:** Each pair in the group is autonomous, and they work in tandem to reproduce a new generation through mating. They each process spiders from various species' mating in the web, as were previously mentioned. Only the strongest or fittest spider in the web lives, though. For the reproduction procedure in this approach, an array is used. This array-based replication is continued until a widow array with random numbers is available. Then, using the following equation, the symbol is indicated for producing an offspring:

$$y_1 = \mu \times x_1 + (1-\mu) \times x_2 \tag{17}$$

$$y_2 = \mu \times x_2 + (1-\mu) \times x_1. \tag{18}$$

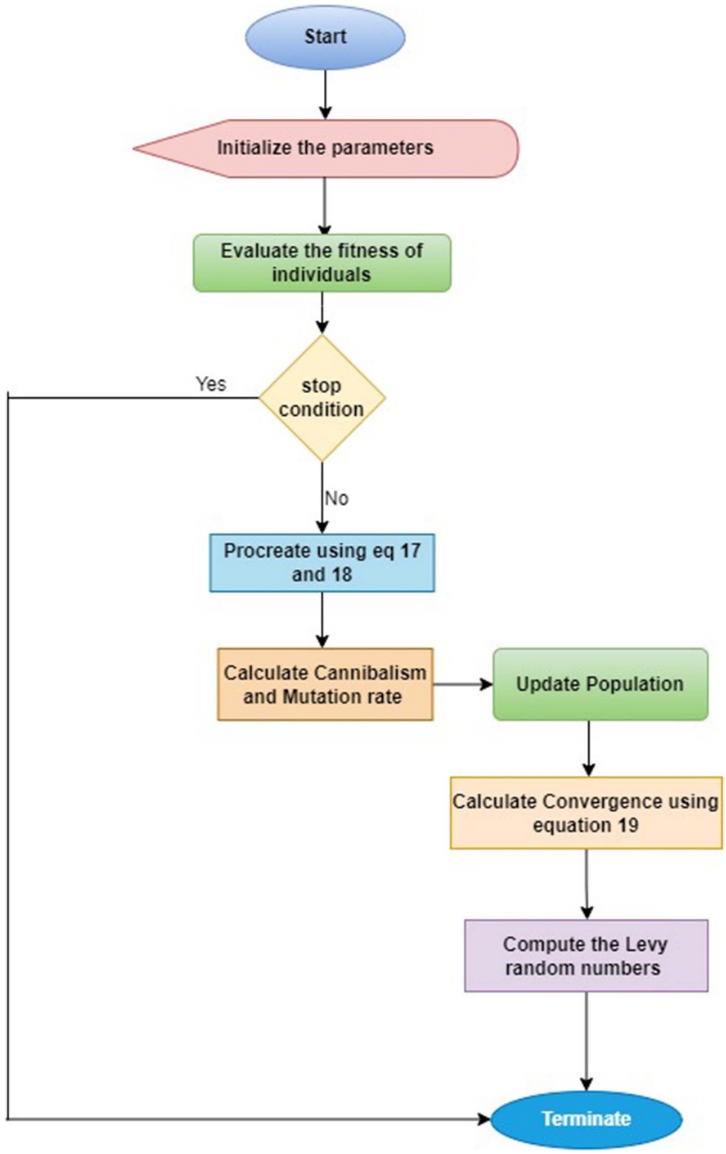

Figure 5. Flow chart of proposed BWO-MFO.

Here i and j can be represented in the range of 1 to N. Whereas μ can be determined in the random range of 0 and 1. The parent individuals are denoted as x_1 and x_2 whereas offspring individuals are represented as y_1 and y_2.

- **Cannibalism:** Sibling cannibalism, child cannibalism, and sexual cannibalism are the three types of cannibalism. In a kind of sexual cannibalism, the female spider eats the male either during or after mating. Here, the significance of fitness is heavily taken into account. The second kind of cannibalism occurs when a youngster consumes their parents to ascertain whether or not the spider lings are weak or powerful. Similarly, sibling cannibalism occurs when a spider consumes its weaker sister. This method calculates the survival rate by determining the cannibalism rate.
- **Mutation:** A mutation approach based on random selection is used to create the population by the muted population number. According to the chosen approach, the figure depicts two array objects that will be switched at random. The mutation rate affects the population of mutations. The procedure for mutation is represented in figure 6.
- **Convergence:** Premature convergence must be avoided to promote population diversity, and the Moth flame optimization method must speed up convergence. The moth-flame has the unusual ability to gradually increase population diversity. This method aids in emerging from the local optimum. Additionally, this approach is effective for MFO exploration and exploitation. Here, the updated Moth flame optimization

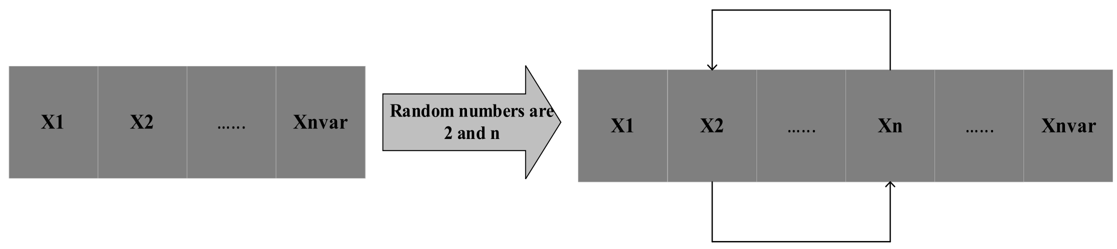

Figure 6. Mutation procedure.

algorithm's convergence process is included based on using the equation below. Below is a diagram illustrating the process' mathematical formulation:

$$X_i^{i+1} = X_i^t + u\text{sign}\left[\text{rand} - 0.5\right] \oplus \text{ Levy}\left(\beta\right) \tag{19}$$

where, X_i^t symbolizes ith solution vector or moth flame, the number of iterations is indicated as X_i. Whereas t, u denotes random parameter is considered for uniform distribution, $\oplus$ denotes dot product (entry wise multiplications). Let rand the random initialization range is [0,1]. The representation is given with the sign [rand $-$ 0.5] where only three values can consider such as 0,1, and -1. The moth flame can do a random walk since the above equation contains the combination of u sign [rand $-$ 0.5]. With the use of the Modified Moth flame in the BWO process, local minima may be decreased and global search capabilities can be increased. Furthermore, the Levy distribution process is supported by the process of the leaps, and the Moth flame process primarily relies on random walks where step length serves to decide the step in its process. The following diagram illustrates how this technique works mathematically:

$$\text{Levy}\left(\beta\right) \sim \mu = t^{-1-\beta}, \quad \left(0 \leqslant \beta \leqslant 2\right). \tag{20}$$

The above equation is to compute the Levy random numbers

$$\text{Levy}\left(\beta\right) \sim \frac{\theta \times \mu}{|v|^{1/\beta}} \tag{21}$$

where μ and v denotes the standard normal distributions and Γ signifies a standard Gamma function. $\beta =$ 1.5, and ϕ is defined as follows:

$$\phi = \left(\Gamma\left(1+\beta\right) \times \sin\left(\pi \times {}^{\beta}/_{2}\right) |\Gamma(((1+\beta)/2) \times \beta \times 2^{(\beta-1/2)}\right)^{1/\beta}. \tag{22}$$

Levy-Flight and Random Walk are combined to eliminate the MFO algorithm's delicate nature. The relationship enhances the capability of the worldwide search. With this procedure, local minimum processes, particularly for benchmark functions for multiple models and single-model functions, may be reduced to produce good results. All of these processes together train the whole network design and lower the error function. The suggested classifier is capable of differentiating multi-classification SA tasks after the training phase. The pseudo-code of the suggested technique is structured in table 3 as follows.

The system's weight factor was determined after a predetermined number of iterations, and it was then used to evaluate the deep learning framework. In turn, this reduces the error function of incorrectly categorized sentiment and has the potential to improve accuracy. Additionally, it was determined that the offered optimization algorithms may produce pleasing results when using the emotional analysis technique since the given classification system produces good results.

5. Experimentation result and discussion

This section outlines the experimental assessment of the suggested strategy for SA using user feedback, sentiment, and opinions on various context free-text data. Text data about sentiment was gathered by big data firms for this study. Python is used to handle the collected data, and suggested algorithm calculates and investigates several connected terms for data classification. The sentiment of various reviews is described using the SA method. The proposed technique was tested using publicly available benchmark datasets obtained from Kaggle.com i.e. Amazon reviews and Twitter comments. The respective datasets description is as follows:

Table 3. Pseudo code of the suggested approach.

Input: Online Reviews
Output: Multi-classification sentimental analysis
//** ***Data Pre-processing*** **//
    Stop word removal;
//** ***SentiWordNetFeature extraction*** **//
    Form feature vector using *equations* (2)–(7);
//** ***Create NH-ResNeXt-RNF framework*** **//
    Procedure
    Predict CLASS
    Establish input and output layer;
    Establish input and output vector components;
        {
        Use NHH to fine-tune the ideal weight and bias function;
        For
        Set the weight and bias factors to zero.
        While stopping requirements not met
        Do
        Evaluate fitness function using $\boldsymbol{fit_n} = \frac{1}{x}\sum_{e}^{x} \boldsymbol{T_e^{(u,v)}} - \boldsymbol{\delta_e}$;
        Update solution using minimum fitness function;
        End for
        End
        Return optimal weight factor
        }
    Return CLASS (label)
    End procedure
End

Table 4. Amazon dataset summary.

Product Name	Review	Rating
Planetwise Flannel Wipes	These flannel wipes are OK, but in my opinion not worth keeping. I also ordered some Imse Vimse Cloth Wipes-Ocean Blue-12 count which are larger, had a nicer, softer texture and just seemed higher quality.	3
Planetwise Wipe Pouch	it came early and was not disappointed. i love planet wise bags and now my wipe holder. it keeps my osocozy wipes moist and does not leak. highly recommend it.	5
Annas Dream Full Quilt with 2 Shams	Very soft and comfortable and warmer than it looks...fit the full size bed perfectly...would recommend to anyone looking for this type of quilt.	5

5.1. Data set description

Amazon products are rated on a 5-star scale. The dataset contains a total of approximately 1,80,000 reviews, with 80% used for training and 20% used for testing. The reviews were gathered from publicly available Amazon data sources and are shown in table 4.

Kindle: Short Twitter datasets for SA in exactly the same way that the Kindle Store dataset. It contains 982 619 product reviews and metadata from Amazon.

This article describes the mechanism for computing events and presents the average sentiment of published reviews. This section’s experimental results show that the technique is legitimate and compare the suggested method to already-in-use methods. Evaluation parameters including Accuracy, Precision, Sensitivity, Recognition Error, Specificity, F1-score, and Processing Time are examined and verified to validate the performance of the suggested technique. In this scenario, 80% of the datasets are used for testing, and 20% of the datasets are utilized for training, with 0.2% of the testing data being used as a validation subset. Simulations are run on the Python working platform using the software multi-class opinions to validate the suggested technique.

On a machine with 12 GB of RAM and an Intel TM core (7M) i3-6100CPU running at 3.70 GHz, the experimental procedure is carried out using the Python tool. In this case, the Python programs Open CV, NumPy, TensorFlow, Keras, and matplotlib were used. OpenCV is used for image processing, including reading and writing to files, NumPy is used for matrix manipulation, TensorFlow is used for backend packages, Keras is used to construct high-level interfaces, and Matplotlib is used to plot graphs. It serves as a testing ground for the planned automatic categorization system and is a developing open-source standard.

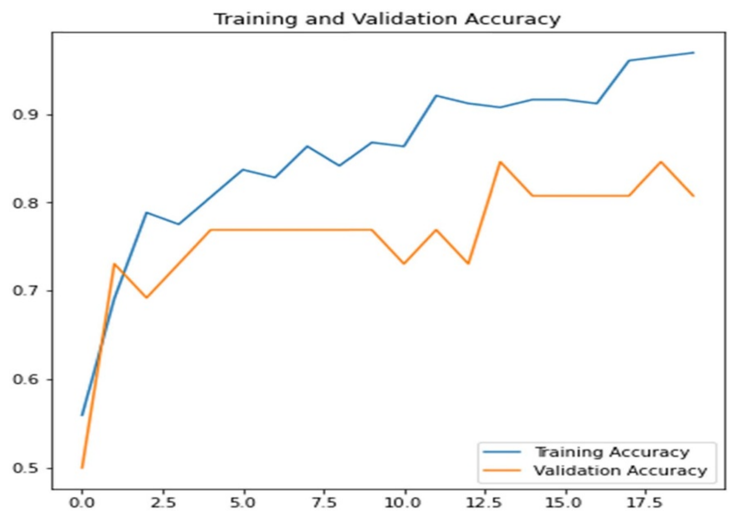

Figure 7. Simulation outcome of accuracy measure.

The testing phase accounted for 20% of the Kaggle dataset, whereas the training procedure accounted for 80%. The training procedure took 103.864 32 s to complete, while the suggested emotional analysis assignment took 9.71 s to process. Additionally, by contrasting the assessment metrics of the suggested approach with those of the current techniques, the predictive model's efficacy is confirmed. The evaluation metrics are calculated using the confusion matrix derived from the experimental results. As assessment metrics for this analysis, Processing Time, Accuracy, Precision, Specificity, Sensitivity, F1-score and Error are used.

5.2. Evaluation metrics

Our suggested NH-ResNeXt-RNF model is put to the test using standard performance evaluation. The primary metrics used to assess our model are listed below. The following metrics can be used to evaluate the model:

- Accuracy: It is described as the percentage of all accurately classified cases in relation to all instances:

$$\text{Accuracy} = \left(\frac{(\text{Tp} + \text{Tn})}{(\text{Tp} + \text{Tn} + \text{Fp} + \text{Fn})}\right).$$

- Precision: It is described as the proportion of correctly classified positive cases to all positively anticipated instances:

$$\text{Precision} = \left(\frac{\text{Tp}}{(\text{Tp} + \text{Fp})}\right).$$

- Recall: It is described as the portion of correctly classified positive cases relative to the overall positive instance count:

$$\text{Recall} = \left(\frac{\text{Tp}}{(\text{Tp} + \text{Fn})}\right).$$

- F1-score: It may be characterized as the typical harmonic of precision and recall:

$$\text{F1- score} = \left(\frac{2\,(\text{Recall} \times \text{precision})}{\text{Recall} + \text{precision}}\right).$$

5.3. Performance analysis of proposed model

The evaluation measures sensitivity, specificity, precision, accuracy, processing time for the F1-score, and loss functions are computed in the following sections to evaluate the suggested model by comparing it to the existing methodologies. The next sections offer the overall results obtained and comparison graphs of the proposed and current classification systems. The figure 7, demonstrate the accuracy graph of proposed approach.

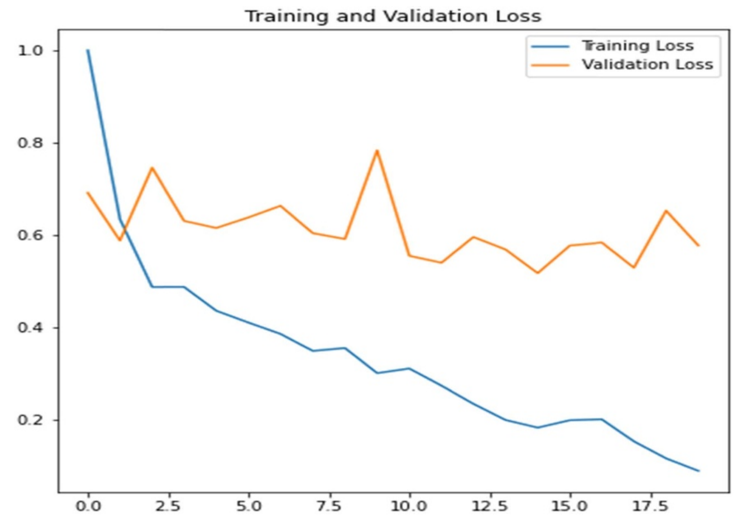

Figure 8. Proposed outcome of the loss function.

Table 5. Performance evaluation of the suggested and current prediction systems.

	Classifier				
Predictive model	Accuracy	Precision	Sensitivity	Specificity	F1-score
DGFLP [16]	67.92	70	72.54	75.83	68.35
Latent space data fusion method [18]	93.56	91.84	87.76	90.48	89.16
Sentiment classification model [19]	89.74	83.81	85.92	85.49	85.93
AL-SSVAE [20]	88.98	87.06	87.42	76.28	85.21
SenticNet [21]	65.5	64.95	65.91	63.75	64.79
SITO [22]	65.34	65.71	64.28	64.19	65.95
The proposed NH-ResNeXt-RNF	96.48	99	95.36	96.12	96.5

The results of the training and validation for the accuracy metric are shown in figure 7. The blue and orange lines in the accompanying diagram represent, respectively, training and validation accuracy. It appears that changing the number of iterations causes the acquired accuracy measure to progressively rise and continue to rise, showing improved prediction results. For instance, the training and validation accuracy is approximately over 95% when the iteration reaches the 15th number of iterations. Similarly, the resultant classification outcome for training and validation loss is shown visually in figure 8:

The results of the proposed deep learning technique's loss function (prediction error), which achieves the lowest possible error function, are shown in figure 8. For instance, the prediction error of the suggested solution drops from 1.0 to 0.2 when the iteration is increased from 0 to 17.5. In terms of accuracy and error function, it, therefore, performs better. The suggested methodology is contrasted with current methods and examined in the following sections for clarity.

5.4. An overall analysis of proposed and current methods

Comparisons are made between the proposed deep learning method and existing methods such DGFLP, Latent Space Data Fusion Method, sentiment classification model, AL-SSVAE, SenticNet, and Social Impact Theory-based Optimization (SITO).

The table above (table 5) shows a general comparison of deep learning and machine learning methods for sentimental analysis classification. The error function and processing time have both been greatly reduced by the suggested technique. Additionally, the suggested strategy outperforms previous strategies in terms of assessment parameters including accuracy, sensitivity, precision, and specificity. The proposed optimized NH-ResNeXt-RNF technique achieves 96.48 accuracies, and accuracy for the other existing approaches such as DGFLP, Latent Space Data Fusion Method, sentiment classification model, AL-SSVAE, SenticNet, and SITO, the accuracy is obtained as 67.92, 93.56, 89.74, 88.98, 65.5, and 65.34 respectively.

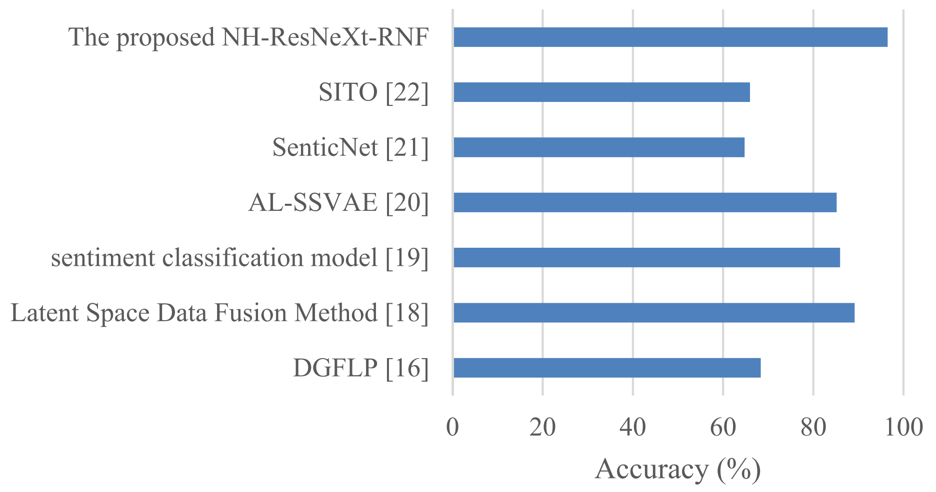

Figure 9. Comparison analysis of accuracy metric.

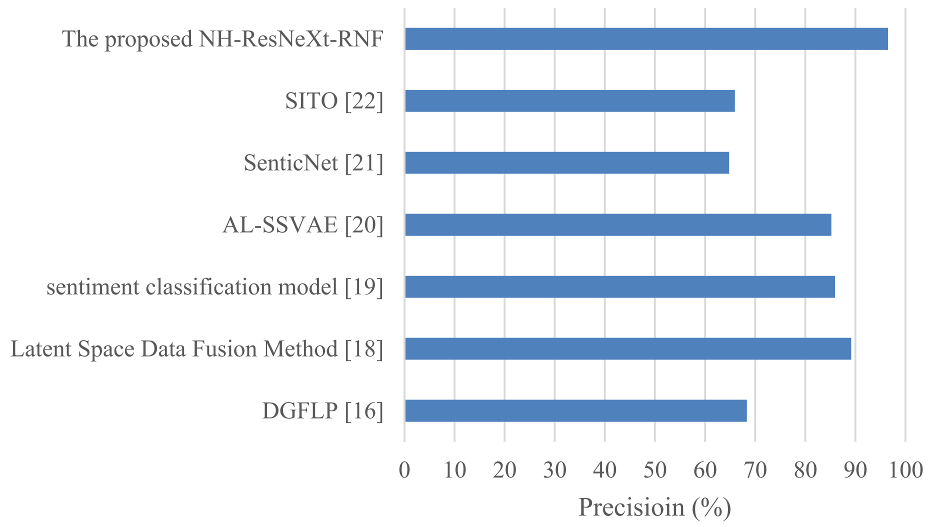

Figure 10. Comparison analysis of precision.

The comparative examination of several methodologies with terms of accuracy is demonstrated in the preceding figure 9. The comparison graph reveals that the proposed method can effectively classify the SA. The accuracy of the suggested method is obtained as 96.48% which is superior to the other exiting system. The accuracy of the SITO is less than the other compared approach taken for comparison which is 65.34.

The comparative examination of several methodologies based on precision is shown in the above figure 10. The comparison graph reveals that the suggested method outperformed well for classification SA. The precision of the proposed method is obtained as 99% which is superior to the other exiting system. Whereas, SENTICNET achieved less precision.

The results of the sensitivity tests are shown in figure 11. SenticNet achieves 65.91 sensitivity. The SITO achieves 64.28 measures of sensitivity which is low compared to other approaches. However, the suggested approach achieves a sensitivity of 95.36 which is superior to the other existing approach.

The results of the specificity tests are shown in figure 12. SenticNet SITO achieves 63.75 and 64.19 measures of specificity respectively which is low compared to other approaches. However, the proposed method achieves a specificity of 96.12 which is superior to the other existing approach.

The comparison of several techniques based on F1 score is illustrated in the accompanying figure 13. The comparison graph shows that the suggested strategy performed better than expected for classifying SA. The F1-score of the proposed method is obtained as 96.5% which is superior to the other exiting system. On the other hand, SENTICNET achieved less F1-score that is 64.79. The error values are given in table 6.

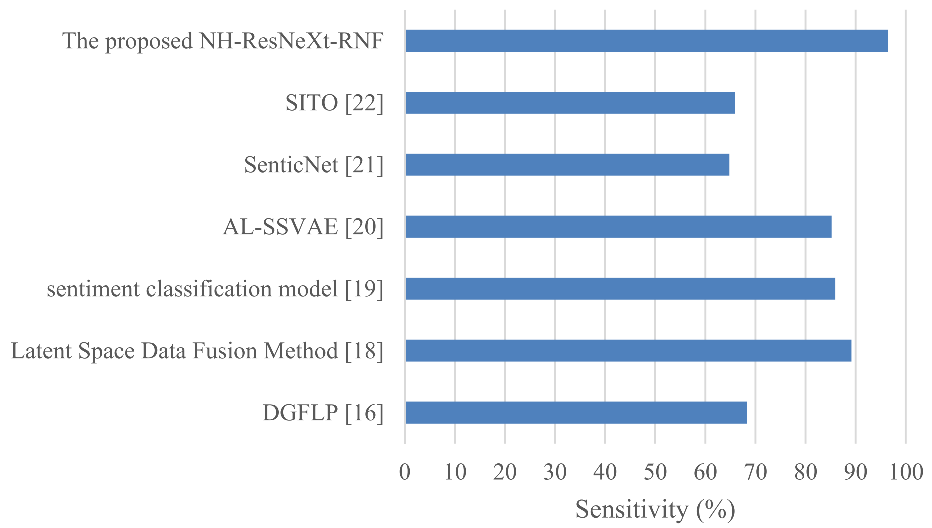

Figure 11. Outcome of sensitivity.

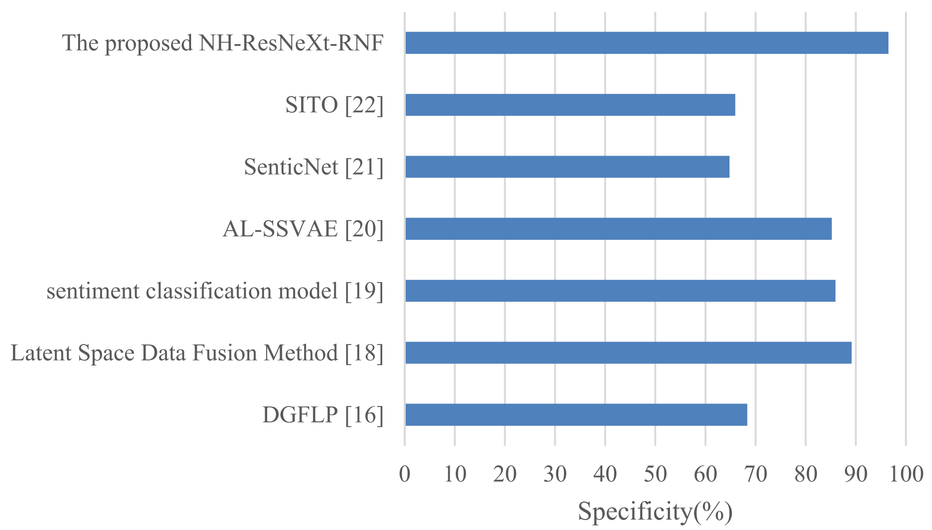

Figure 12. Outcome of specificity measures.

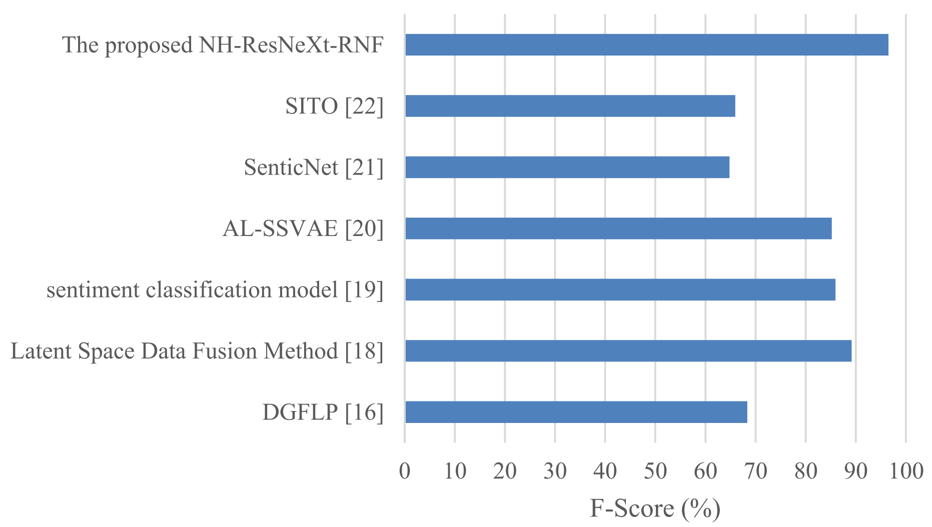

Figure 13. Outcome of F1-score measures.

Table 6. Error values.

Predictive model	Error
DGFLP [16]	0.95
Latent space data fusion method [18]	0.92
Sentiment classification model [19]	0.98
AL-SSVAE [20]	0.86
SenticNet [21]	0.59
SITO [22]	0.14
The proposed NH-ResNeXt-RNF	0.039

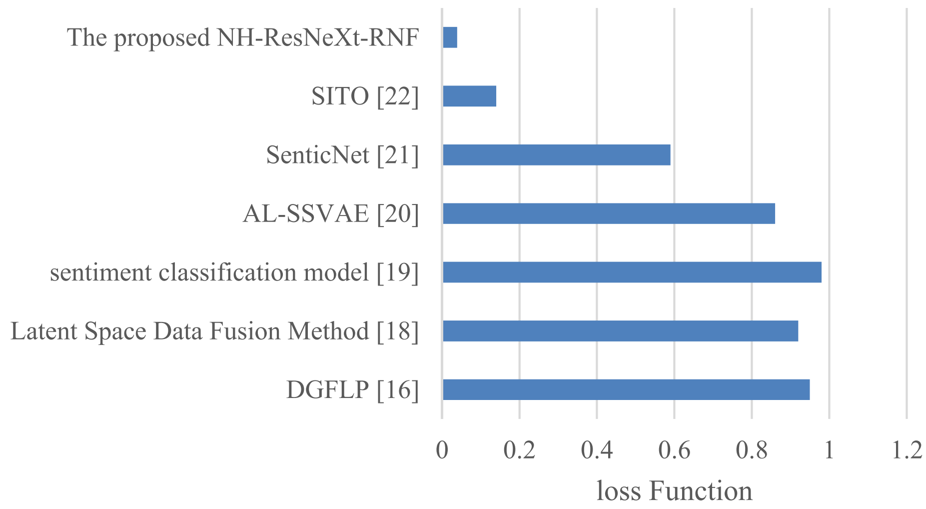

Figure 14. Obtained loss function of proposed and existing schemes.

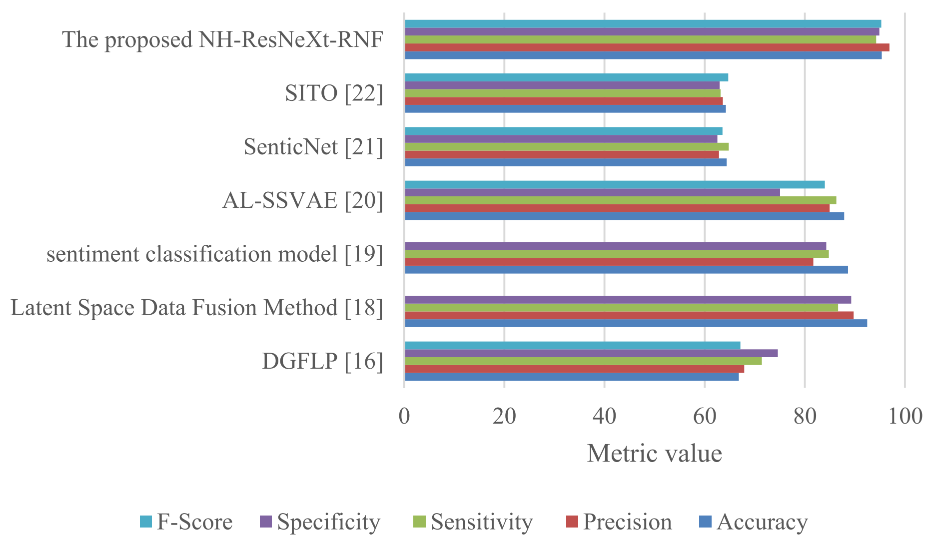

Figure 15. The performance metric values of proposed model on Twitter dataset.

Figure 14 depicts the proposed and existing outcome of a sentimental analysis classification system in terms of the loss function. The proposed method yields a loss measure of 0.039, which is very low. The examination as a whole lead to the conclusion that the suggested deep learning method achieves a superior result for the sentimental model analysis. In this work, the author discussed the sentimental analysis approach using the NH-ResNeXt-RNF framework. The author also demonstrates how this technology can be used to categorize various types of sentiments.

The proposed NH-ResNeXt-RNF method applied on Twitter dataset and the respective metric values are listed table 2. With respect to every respective metric, the suggested method is outperformed when compared with state-of-art methods. This effect is clearly shown in figure 15. The performance of proposed method

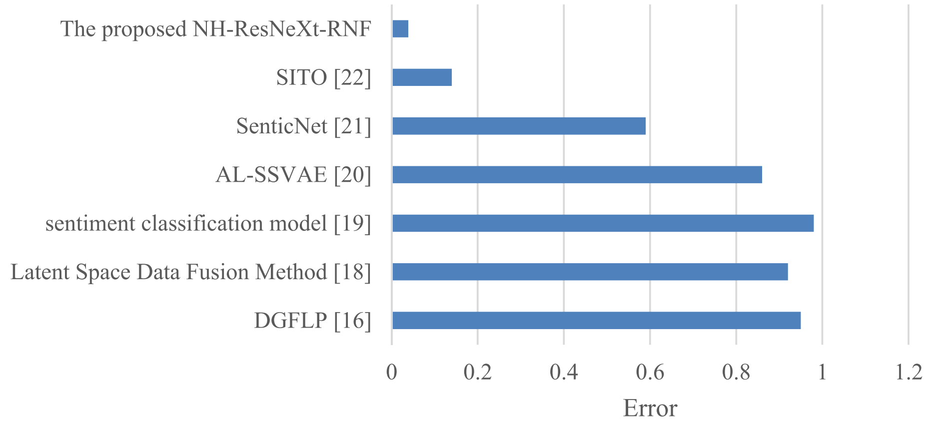

Figure 16. Comparison of proposed model with state-of-art models in terms of error.

evaluated on two datasets namely: Amazon and Twitter dataset. When compared to the results of both the datasets, the proposed method has high values on the Amazon dataset. Even though the Amazon dataset is complex, the proposed model has high performance metric values due to its hybrid nature. The proposed model is compared to state-of-the-art model in terms of error is represented in figure 16.

6. Conclusion

The major goal of this research is to use the proposed NH-ResNeXt-RNF model to assist the sentimental analysis approach in an e-commerce application. The suggested model begins with the data pre-processing stage to transform raw data into an understandable format. With the help of Senti-WordNet, only relevant sets of features are extracted from the pre-processed outcome. As a result, an effective feature vector is generated. Finally, in order to effectively classify the multi-class sentiment, the extracted features are fed as input to the proposed NH-ResNeXt-RNF framework. The proposed methodology optimally tunes the parameters involved in the classification system. Thus, the proposed NH-ResNeXt-RNF assists the system to classify multi-classification sentiments and is improved by utilizing the Black widow-Moth flame optimization approach. The proposed model achieves an accuracy of 0.9648 and a loss function of 0.039 respectively, which is more effective than existing techniques. In future research, the author will adopt a feature selection approach to further improve the classification performance.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://www.kaggle.com/datasets/sameersmahajan/reviews-of-amazon-baby-products and www.kaggle.com/datasets/bharadwaj6/kindle-reviews.

Conflict of interest

The authors of this paper state that they have no affiliations with any businesses whose goods or services could be connected to the topic of the study.

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Guarantor

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Statistics and biometry

For this work, simple statistical techniques were sufficient.

Informed consent

Only if the study is on human subjects

For this investigation, informed permission was not needed in writing.

Only if the study is on animals

It was not necessary to get permission from the university animal care committee.

Ethical support

There was no requirement for Institutional Review Board clearance.

Research involving human participants and/or animals

Not essential.

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