Customer Satisfaction Analysis based on Online Products by their Emotion Recognition using Meta Heuristic MachineLearning Algorithms

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Received: 09.04.2024 Revised : 17.05.2024 Accepted: 26.05.2024

ABSTRACT
In the modern corporate world, customer satisfaction is crucial for establishments. There are manual techniques, such as surveying clients and giving them questionnaires. On the other hand, companies and marketers are searching for rapid methods to obtain useful and efficient feedback for their prospective clients. Analysing evaluations by hand in order to make choices and go over business models is difficult. Natural language processing (NLP) allows users to analyse and automate this process, though.This research proposes novel technique in online product-based customer satisfaction analysis by emotion recognition using meta-heuristic machine learning (ML) model. Input is collected as online product-based customer reviews and processed for noise removal, normalization and missing value removal. Then this data feature extraction is carried out using convolutional regressive LSTM Gaussian model and classified using particle transfer graph swarm wolf optimization model. the classified output shows the detected emotion of the customer review and their satisfaction-based analysis. Experimental analysis is carried out in terms of average accuracy, mean precision, recall, F-1 score, RMSE.The proposed technique average accuracy 99%, mean precision 96%, recall 95%, F-1 score 94%, RMSE 58%.

Keywords: online product, customer satisfaction analysis, emotion recognition, machine learning model, LSTM Gaussian model

INTRODUCTION

By tracking customer happiness, businesses may tailor their offerings, relationships with customers, and services to better suit their needs. A happy customer is a devoted customer, which equates to more sales and, consequently, turnover. Manual approaches like focus groups, interviews, and satisfaction surveys can be used to gauge customer satisfaction. In terms of cost, time, and data reliability, these procedures are not successful or efficient. Nonverbal communication is facilitated by facial expressions. They are a unique method for us to convey our feelings and gratitude. Negative feedback emotions are frequently associated with a lower perceived quality of service in the context of customer satisfaction [1].A facial expression makes up 55% of what is communicated through speaking. Furthermore, vocal feedback can be understood in 70–95% of cases. Businesses have always been curious about how customers make decisions about what to buy, how they respond to products, what catches their eye, and what goes unnoticed. Understanding and improving user happiness are critical goals in today's world of technology-driven interactions. The growing prevalence of digital lifestyles in society has led to the recognition of user satisfaction as a critical component supporting the success of applications and services. Due to the world's fast urbanisation and rising internet penetration through the usage of smart computing devices, e-commerce portals and online shopping have emerged as society's new marketplaces [2].Customers assess goods and services using several criteria. Reviews, advertisements, or specifications can all be used as forms of evaluation. One of the most significant elements influencing sales of goods and services is reviews. Reviews in the e-Commerce sector assist reduce consumer anxiety about fraud and increase trust between customers and companies. Users can anticipate the kind of review and the product experience by using Natural Language Processing (NLP). Owing to the high frequency of phoney or two-word evaluations on e-commerce sites, a careful investigation and analysis are essential. Customers can

use natural language processing (NLP) to assess a service or product's quality without having to read every review [3].When there are numerous identical items with reviews, it can take a while for humans to analyse these reviews, and choosing the product that will provide the answer is crucial. Having realised this necessity, our research aims to employ deep learning and artificial intelligence (AI) to analyse and detect customer pleasure from facial expressions. Online platforms and apps have developed into complex, service-rich ecosystems where the user experience is paramount [4]. In fact, the success or failure of these platforms can be determined by the calibre of their user experience.In light of this, our research delves into the investigation of facial expression analysis and emotion identification, ultimately aiming to build a sophisticated system that can evaluate user happiness in real time [5].
Contribution: To suggest a novel method for analysing consumer happiness with online products by utilising a meta-heuristic deep learning model to recognise emotions. Here, consumer reviews from online products are gathered as input, and it is then processed for noise reduction, normalisation, and missing value elimination. Next, a particle transfer graph swarm wolf optimisation model is used for classification after the data features are extracted using a convolutional regressive LSTM Gaussian model.

RELATED WORKS

Recommendation systems have also benefited greatly from machine learning in recent years [6]. By taking a customer's face and deciphering its meaning, machine learning can identify emotions using facial expression recognition. Subsequently, the potential customer's emotional condition can be readily detected by automated emotion evaluation. Expressions on the face and lips are used to identify emotions. People typically elicit identical expressions with local changes in response to similar stimuli [7]. We frequently employed two techniques: face distortion and the motion-based method. For the motion-based technique, the change of face is considered. Conversely, with the deformation-based technique, we consider two images: one neutral and one different.The authors of [8] categorise emotions using elements from the Face Action Code System (FACS). Their model counts photos that the system has successfully classified and weighted. They discovered that 2% of the images—six in total—completely failed the tracking test. The average correct recognition ratio was likewise claimed by them to be 91%. Alternatively, a model that can use voice content is developed in [9]. To calculate the Human Computer Interaction (HCI), they develop a system. They use 38 subjects of affect recognition approach with 11 affect states linked to HCI to test their model. Their model's average recognition accuracy for the bimodal fusion was 90%. Feature extraction in [10] uses appearance-based and geometric models. In the first model, features related to the mouth, nose, eyebrow, and eye are extracted. The second model, though, only covers that particular area of the face. Additionally, they use Bayesian networks, SVM, ANN, KNN, HMM, and sparse representation-based classification to assess their model. For instance, authors use KNN to categorise emotions in [11]. Following that, they discover accuracy in the JAFFE and CK+ of 76.7442% and 80.303%, respectively, demonstrating the success and viability of their methodology. To categorise emotions, authors in [12] also use Multi-Layer Perceptrons and Decision Trees. Convolutional neural networks, they discover, provide the best recognition accuracy. For visual emotional analysis, one of the most used tools is the Affdex from Affectiva [13].It makes it possible to provide an individual's emotional trend by using Microsoft Cognitive Services built on the Azure platform and emotion detection. According to Work [14], a customer's conduct and perception can vary depending on their origin, including the linguistic group they speak. Additionally, the way that patrons behave depends on the reason for their trip or use of the hotel's amenities. Customer happiness is also significantly influenced by the quality of the products. A product's quality can be determined simply by asking whether or not it meets the needs of the consumer and whether or not it meets the customer's expectations.Numerous studies have been carried out by researchers that have looked into hidden variables such quality in addition to the vocabulary, subjectivity, and objectivity. In their research endeavours, authors [15] have employed substantial volumes of unlabelled data. It has been noted that using NLP in conjunction with a neural network model produced results with good accuracy; the accuracy improvement is dependent on the cost of processing resources. In addition, the author has included several suggestions for cost-cutting based on thorough investigation.The deep learning algorithms [16] are used to analyze the sentimental analysis during the COVID'19 [17]. To enhance the performance of the BERT approach in Chinese Sentiment Analysis, it is necessary to incorporate word-level incorporation and inputs. This work aims to enhance Chinese Sentiment Analysis by investigating the contribution of multiple approaches to offer an improved iteration of the ERNIE system [18, 19].

Proposed model in online product-based customer satisfaction analysis by emotion recognition

The model was trained to identify several facial expressions, including those of happy, surprise, neutrality, sadness, and rage, and to process those expressions in real time to determine the corresponding emotion. It is possible to determine whether or not a consumer will be satisfied with a product based on the forecast of their feelings during the purchase process. Fig. 1 shows the suggested model's work flow diagram. The names of the emotions these datasets are linked to are used to separate and store them into various subfolders. 4883 example photos were used in this investigation. Of the sample photos, 25% were utilised for validation and the remaining 75% were utilized to train method. Classifier's accuracy increases with the size of the dataset used to train it. This work has employed the supervised learning technique, in which the training dataset is linked to the relevant labels.

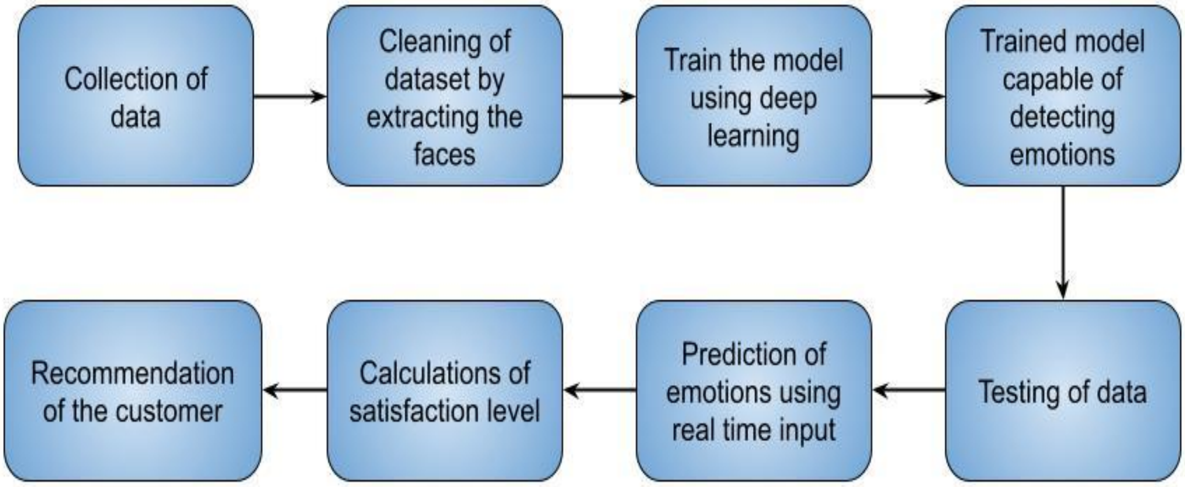

Figure 1. Proposed online product-based customer satisfaction analysis by emotion recognition model

The Python Natural Language Toolkit (NLTK) framework is utilised in our study to mine the gathered comments. A platform called NLTK is used to work with human language data for statistical natural language processing applications. For tokenisation, parsing, classification, stemming, tagging, and semantic reasoning, it has strong text processing libraries. We have measured the polarity of public comments using the Vader method. Vader is a sentiment analysis program that uses rules and a lexicon. C.J. Hutto created the Vader lexicon, which has over 7075 English words as well as a few slang terms and emoticons with polarity scores.

Convolutional regressive LSTM Gaussian (CRLSTMG) model

We also employed them in a continuous sentence matrix to extract high dimensional local features. Two convolutional layers are used in the suggested model (let's say two CNNs). The helpfulness score for every review is determined by applying a second convolution layer to the document representation matrix after the first convolution layer has transformed continuous sentence representation into document representation. For H1, H2, and H3, we chose regions of sizes 3, 4, and 5, respectively. Assume that filter F begins convolving on the generated phrase matrix R1..n for a region size of H. Convolution takes place for every feasible window. The acquired document representation matrix is subjected to the application of the second layer of convolution. This time, we merely employed a single, size-3 filter zone.

After that, every output from the second max-pooling layer was compressed into a single array. Subsequently, three Dense (or fully linked) layers were projected with the inputs from the Flatten layer. All but the final Dense layer was followed by Dropout layers. Dropout is a regularisation strategy where we randomly select a collection of neurones to be dropped throughout each iteration. We merely mean that they don't exist when we drop them. During the training phase, dropout randomly removes neurones with a probability of p in order to prevent over-fitting and accelerate learning. The value p may vary for every layer in the neural network.Because a distinct group of neurones is randomly eliminated for each learning example, this prevents shifting the weights to the same positions and produces a powerful set of features that are better able to generalise with fresh, unseen data. Since our goal was to predict one score for every review, we only kept one neurone in the final denser layer. We gathered each review's final score without using any activation functions at the output stage.

Dependencies maintained over extended periods of time could be found by the LSTM. Gradient problems are resolved by dynamic LSTM/LBU device. Although an LSTM model has fewer nodes, it functions similarly to larger networks that are set up in a particular way.If the faults in a constant error mode are connected to the weight of another mechanism, it is referred to as a Constant Error Carousel (CEC). You will either surpass or fall short of your goal times as the width of your period increases or decreases. The introduction of prior experiences and the identification of the mental illness that causes them, as well as the multiplicative unit, are the two functions of the CEC's phase-in. Recurrent Neural Networks (LSTMs) have been demonstrated to be less effective at modelling long-term dependencies than Standard LSTMs. Once we have more information on the overall design, we will be able to investigate this more. We have to forget about the Gates. This is made feasible by the vectors that link each neurone to the incoming data. This LSTM's ability to combine an input vector (xt) with the previous output vector (h1t-1a) to produce a new output vector (ht1), which is then denoted by the time denotations h1t-1a, is one of its primary features. After the weighted inputs are multiplied and transferred by tanh activation, the output is produced by zt activation by eqn (1)

$$z_t = \tanh(W^z x_t + R^z h_{t-1} + b_z) \quad (1)$$

Results mapped to x and -1 instead of the unweighted ones are obtained while reading from the weight-expanded registers. From them, a sigma activation value is obtained. Through compounding, input to the memory is sent as an extra work as part of output by eqn (2)

$$i_t = \sigma(W^i x_t + R^{z_i} h_{t-1} + b^i) \quad (2)$$

The process of forgetfulness is what an LSTM goes through in order to complete tasks while retaining information from memory that is no longer relevant, which prevents the LSTM from remaining active. This may be anything like, say, forget gate processing x'th, which inactivates weighted inputs via a sigmoidal cross-activation, just before network goes online with a fresh batch of broadcasts. Equations 3 and 4, provide the conventional formulas for isotropic Gaussian and orientated anisotropic Gaussian filters.

$$G(x, y; \sigma) = \frac{1}{2\pi\sigma^2} \exp\left\{-\frac{1}{2}\frac{(x^2+y^2)}{\sigma^2}\right\} \quad (3)$$

$$G\left(x, y; \sigma_x, \sigma_y, \theta = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left\{-\frac{1}{2}\left(\frac{(x\cos\theta + y\sin\theta)^2}{\sigma_x{}^2} + \frac{(-x\sin\theta + y\cos\theta)^2}{\sigma_y{}^2}\right)\right\}\right. \quad (4)$$

Standard deviation (σ) is the only parameter in an isotropic Gaussian filter. Three factors make up an orientated anisotropic Gaussian filter: the angle of orientation (θ), y-axis standard deviation (σy), x-axis standard deviation (σx). A set of Gaussian filters is initially produced for various combinations of σx, σy, and θ to perform filter bank smoothing. After that, set of filters is applied to every pixel in input image, smoothed image is created by choosing maximum filter response at every pixel. An isotropic Gaussian filter with a low standard deviation value can be used to process the smoothed image in order to blend the fine discontinuities.

Particle transfer graph swarm wolf optimization (PTGSWO) model

A text containing l words is represented as T = {r1,...ri,..., rl}, where ri is the ith word's representation. Training can be used to update ri, a vector that is initialized by d dimension word embedding. All of the words that appeared in a given text are considered the nodes of the network that we construct. Every edge begins with one of the text's words and concludes with one of its neighboring words. The graph of text T is specifically described as eqn (5)

$$N = \{\mathbf{r_i} \mid i \in [1, l]\},$$

$$E = \{e_{ij} \mid i \in [1, l]; j[i-p, i+p]\} \quad (5)$$

where word representations in N and edge weights in E are obtained from global shared matrices, and N and E are the graph's node set and edge set, respectively. The symbol p represents the quantity of neighboring words linked to every word on the graph. In addition, to ensure that the parameters are sufficiently trained, we uniformly map all edges in the training set that occur fewer than k times to a "public" edge. gathers data from neighboring nodes first, then modifies its representations using the information it has already gathered and its initial representations, which is described as eqn (6)

$$\mathbf{M_n} = \max_{a \in \mathcal{N}_n^p} e_{an}\, \mathbf{r_a}$$

$$\mathbf{r_n'} = (1-\eta_n)\mathbf{M_n} + \eta_n \mathbf{r_n} (6)$$

where max is a reduction function that combines the maximum values on each dimension to generate a new vector as an output; Mn ∈ R d is the messages that node n gets from its neighbors. N p n indicates nodes that correspond to the closest p words of n in the source text; ean∈ R 1 indicates the edge weight between node a and node n, which is modifiable during training; and rn∈ R d indicates node n's previous representation. For node n, ηn∈ R 1 is a trainable variable that represents the amount of information that should be retained about rn. The updated representation of node n is indicated by r 0 n. The input layer of the original GCN is composed of the input adjacency matrix of the graph and the input feature matrix. An adjacency matrix is provided in order to express the reference link between the nodes. Assume that the input feature matrix is X ∈ R N×D, where D denotes the dictionary set size of V and N its size. When a word is at the m-th position of the dictionary set, it can be stated as Xim = {01,..., 0m−1, 1m, 0m+1,..., 0D} in the i-th node. Let A∈ R N×N be the self-loop adjacency matrix of graph G. The original GCN's hidden layer can gather the node data from the current layer and forward the features to the next layer by employing propagation rules. The features grow more abstract as they penetrate ever deeper buried strata. The layer-wise propagation rules of the i-th node can be expressed as follows by eqn (7)

$$h_i^l = \sigma\left(\sum_{j=1}^{N} \bar{A}_{ij} \cdot W^l \cdot h_i^{l-1} + b^l\right)$$
$$\bar{A} = D^{-\frac{1}{2}} \cdot A \cdot D^{-\frac{1}{2}}$$
$$D_{ii} = \sum_{j=1}^{N} A_{ij} \qquad (7)$$

After gathering the final features of the hidden layer, the output layer of the original GCN may use the softmax function to calculate the probability value of each category. The maximum value of the probability can then be used to categorize the text. Given a sentence of k words, S = {W1, W2,..., Wk }, the model embeds the original input text using the pre-trained embedding matrix. Next, we can derive the text feature representation matrix M ∈ R k×d, where d is word embedding dimension and k is sentence S's vocabulary size.

There is usually a bird that has a keen sense of smell, so it knows exactly where the food is and has the right food resource message. The birds will eventually congregate in the location where food is located because they are always communicating, especially when it comes to vital information, as they move from one location to another in quest of food. This method of calculating global optimisation functions/problems is derived from the behaviour of animals, and each member of swarm/crowd is referred to as a particle. Two mathematical equations are used in the PSO technique to update every partner of crowd's position in global search space by eqn (8)

$$v_i^{k+1} = v_i^k + c_1 r_1\left(p_i^k - x_i^k\right) + c_2 r_2\left(g_{\text{best}} - x_i^k\right)$$
$$x_i^{k+1} = x_i^k + v_i^{k+1}$$
$$d = \left|c \cdot x_{p(t)} - x(t)\right|$$
$$x(t+1) = x_{p(t)} - a \cdot d \qquad (8)$$

The following is the mathematical formulation for the vectors a and c by eqn (9)

$$a = 2l \cdot r_1$$
$$c = 2 \cdot r_2 \qquad (9)$$

The process of locating global optima is a difficult one. Two effective methods are provided for suggested methodology. First method is PSO, in which people are prompted to move based on both their local and global optimal places. The population's best position is known as global best position, whereas an individual's best position to date is known as local best position. People in PSO are able to converge on their global aim because of their social behaviour. The fish school and bird flock in nature have an impact on this behaviour. We chose PSO for our suggested hybrid optimiser because of its power, dependability, and ease of use. Second optimiser in our suggested hybrid strategy is a grey wolf optimiser. GWO is a swarm-based metaheuristic optimiser that mimics social structure and foraging habits of grey wolves. People who are transferred inside GWO are impacted by alpha, beta, delta positions of three leaders. In our hybrid optimiser, the optimisation process starts with a randomly selected set of individuals. These individuals have been suppressing potential fixes for the issue at hand. First three leaders are given labels alpha, beta, and delta once the fitness function for each iteration has been established for every person. After that, the population is divided equally into two classes: the first class is organized according to the GWO processes, and the second class is organized according to the previously mentioned PSO procedures. This leads to a thorough scan of the search area for potential spots, which are then exploited with the help of the potent PSO and GWO. Figure 2 shows the flowchart for the suggested PTGSWO algorithm.

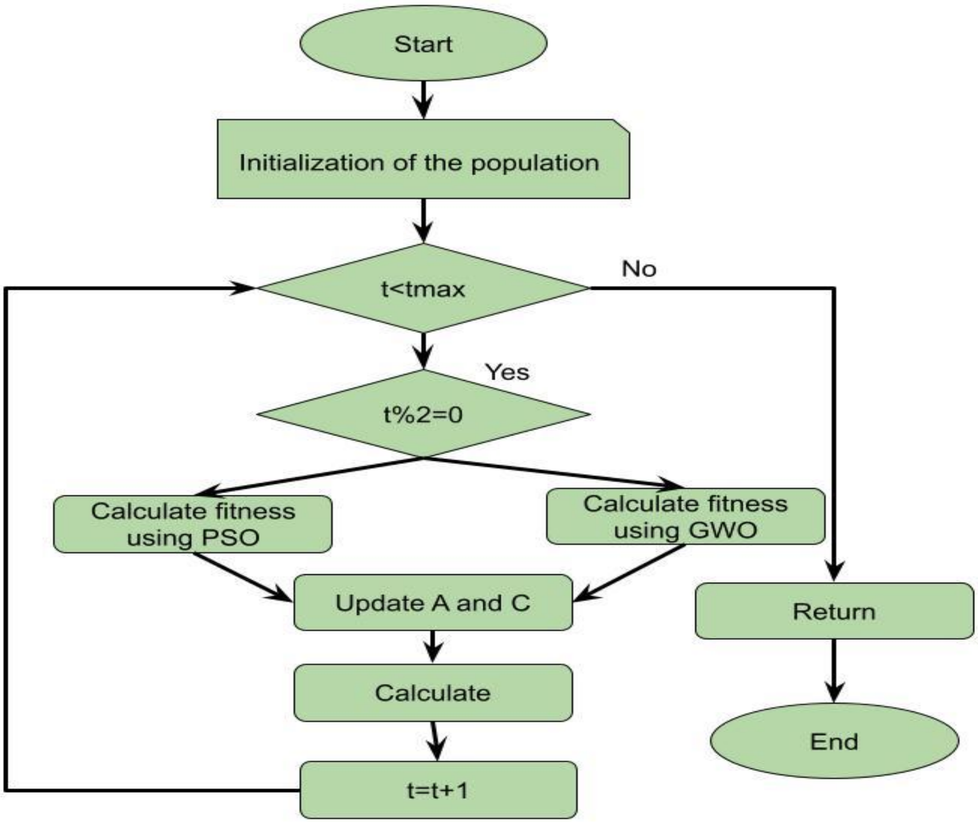

Figure 2. Flow-chart for proposed PTGSWO algorithm

Experimental analysis

simulation setup-The suggested pseudocode is implemented on Intel HD Graphics, 15.6′′ 3GB Memory, i5 Processor 430M, 16.9 HD LCD, Pentium-Intel CoreTM, and 320GB HDD. It is coded in MATLAB R2013a. The parameters c1 = c2 = 0.5 and c3 = 0.5, w = 0.5 + rand()/2, and l ∈ [2,0] are all utilized to test the effectiveness of hybrid and other metaheuristics. There are 30 search agents and a maximum of 500 iterations.

Dataset description:Through product reviews, we may also discover user opinions about goods and services on e-commerce sites. Product evaluations have a significant influence on purchasing decisions. Since its founding in 2009, Tokopedia has grown to become one of Indonesia's leading e-commerce platforms. In second quarter of 2021, Tokopedia's webpage received 147 million views, with Shopee coming in second with 126 million. Less than 30 million online views were attained by Blibli, Bukalapak, and Lazada, three other e-commerce rivals. A compilation of Tokopedia product reviews makes up PRDECT-ID. Product Reviews Dataset for Emotions Classification Tasks - Indonesian is referred to as PRDECT-ID. PRDECT-ID has 5400 product reviews in total. Human language relies heavily on emotion to convey a particular view of a circumstance or state of affairs. It also has a significant impact on unique experiences, such online purchasing. Five fundamental emotion categories—love, happiness, anger, fear, or sadness—were identified in their research. Most emotions have a lexicon of terms associated with them. For example, the terms "pity," "sympathy," and "shame" are connected to melancholy. Another illustration is how words like "envy," "hatred," and "distrust" are connected to fury. Shaver's emotions model is used to annotate each product evaluation with a particular emotion.Because it is easy to use and extremely effective for creating a computational emotions model, Shaver's emotions model is widely used as the standard for categorizing emotions. Based on the content of the customer reviews, the annotator labels each product review. The annotating procedure adheres to the emotional annotation guidelines developed by clinical psychology professionals and lecturers.

Instituto de Matematica Pura e Aplicada Face 3D created the IMPA-FACE3D dataset in 2008. They use the six universal expressions—sadness, fear, anger, surprise, and disgust—that Ekman recommended. They created graphics that included colour and geometric information, demonstrating the correlation between texture and geometry. This dataset includes samples for six different facial expressions as well as a neutral face sample. They created pictures with 16 ladies and 22 males. Most of these individuals are in the age range of 20 to 50.

The dataset can be downloaded via an Amazon open-source resource. Various product categories, including sports, toys, technology, books, movies, and more, are included in multiple packages. The dataset that we are working with is derived from product reviews for electronics. While there are approximately over a million potential cases, we only gathered 10,000 cases. The information was gathered from US marketplaces, and every product and customer have an own ID. On a scale of 1 to 5, 1 represents the lowest rated product and 5 represents the highest. The actual information offered by customers about their reviews of the product may be found in the *aeview_body*.
We employ a widely recognised and utilised facial expression dataset. In fact, the effectiveness of our approach is assessed in this work using the enlarged Cohn-Kanade database (CK+)6. There are several photos in this database that include labels for different expressions. 327 picture sequences representing the emotions "Happy," "Surprised," and "Neutral" may be found in the CK+ database.

Comparative analysis

Table 1. comparison between proposed and existing technique for various online product based customer satisfaction analysis by emotion recognition

Dataset	Techniques	Average accuracy	Mean precision	RMSE	Recall	F-1 score
PRDECT-ID	CNN	68	70	78	74	73
	SVM	77	75	74	80	79
	CRLSTMG_PTGSWO	83	81	65	85	82
IMPA-FACE3D Dataset	CNN	75	77	82	70	74
	SVM	79	82	72	81	83
	CRLSTMG_PTGSWO	85	88	66	87	86
AMAZON Dataset	CNN	79	81	83	80	78
	SVM	83	85	79	84	88
	CRLSTMG_PTGSWO	91	89	60	89	93
CK+	CNN	83	86	68	85	82
	SVM	89	92	64	91	86
	CRLSTMG_PTGSWO	99	96	58	95	94

Table-1 shows comparative analysis various online product based customer satisfaction analysis by emotion recognition dataset. Here the online product based customer satisfaction analysisdataset analysed are PRDECT-ID ,IMPA-FACE3D Dataset and AMAZON DATASET, CK+ dataset in terms of Average accuracy, Mean precision, RMSE, RECALL , F-1 SCORE.

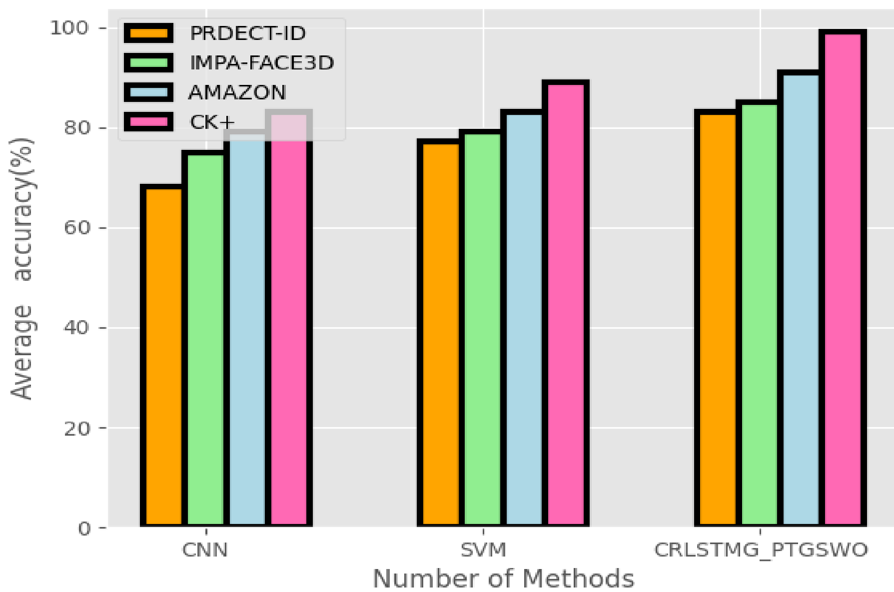

Figure 3. comparison of Average accuracy

The analysis for average accuracy is displayed in Figure 3. Here, the proposed technique achieved 83% average accuracy, 68% existing CNN, and 77% SVM for the PRDECT-ID dataset; for the IMPA-FACE3D Dataset, the proposed technique achieved 85% average accuracy, 75% existing CNN, and 79% SVM; for the AMAZON Dataset, the proposed technique achieved 91% average accuracy, 79% existing CNN, and 83% SVM; the proposed technique attained 99% average accuracy, 83% existing CNN, and 89% SVM for CK+ dataset.

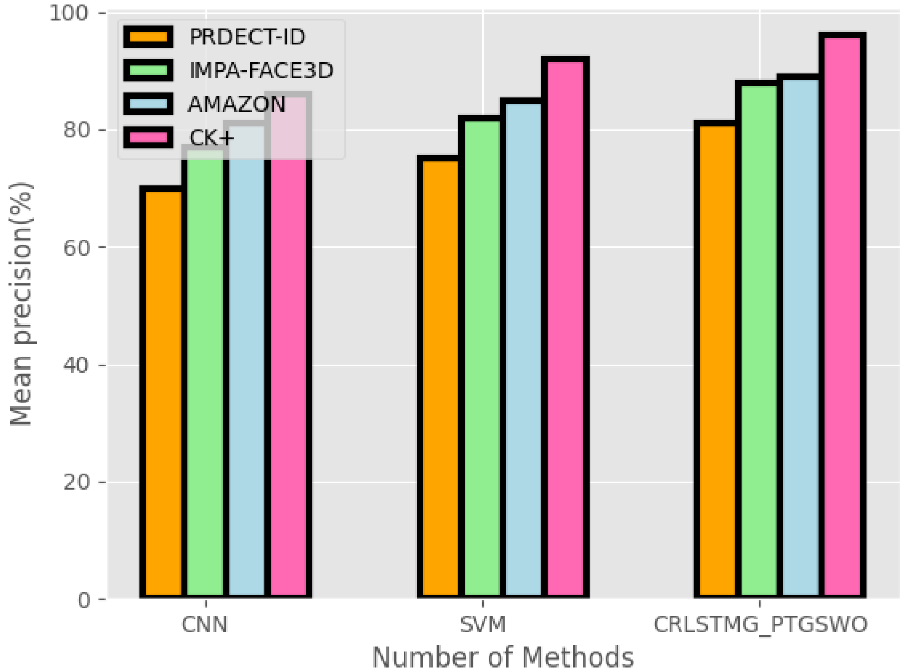

Figure 4. comparison of Mean precision

Figure 4 shows analysis in Mean precision. Here proposed technique Mean precision of 81%, existing CNN 70%, SVM attained 75% for PRDECT-ID dataset; for IMPA-FACE3D Dataset proposed technique Mean precision of 88%, existing CNN 77%, SVM 82%; proposed technique Mean precision of 89%, existing CNN 81%, SVM 85% for AMAZON Dataset; for CK+ Dataset proposed technique Mean precision of 96%, existing CNN 86%, SVM 92%.

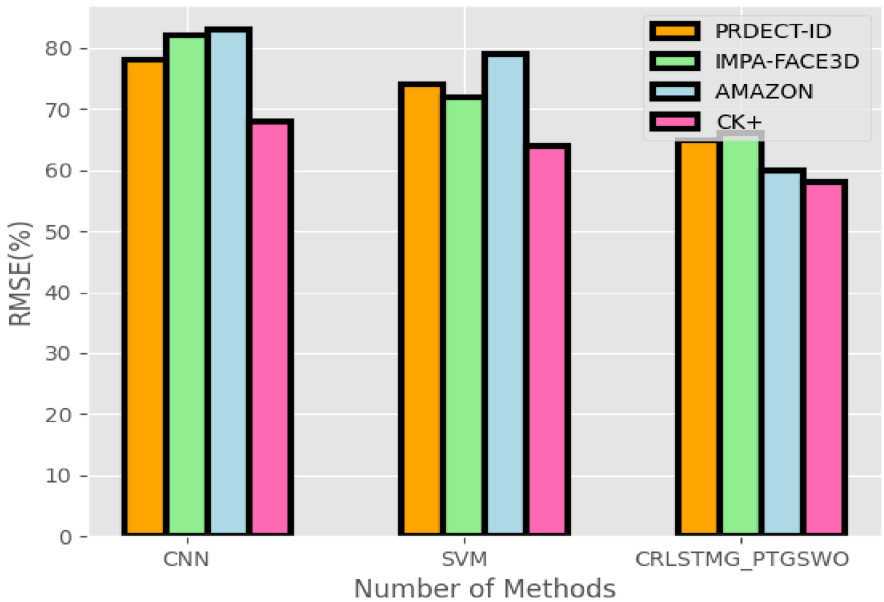

Figure 5. comparison of RMSE

Analysis in RMSE is shown in Figure 5. In the PRDECT-ID dataset, the proposed technique obtained RMSE of 65%, the existing CNN attained 78%, and SVM attained 74%; in the IMPA-FACE3D dataset, proposed technique obtained RMSE of 66%, the existing CNN attained 82%, and SVM attained 72%; in the AMAZON dataset, proposed technique RMSE of 60%, the existing CNN attained 83%, and SVM attained 79%; the CK+ dataset, proposed technique RMSE of 58%, the existing CNN attained 68%, and SVM attained 64%.

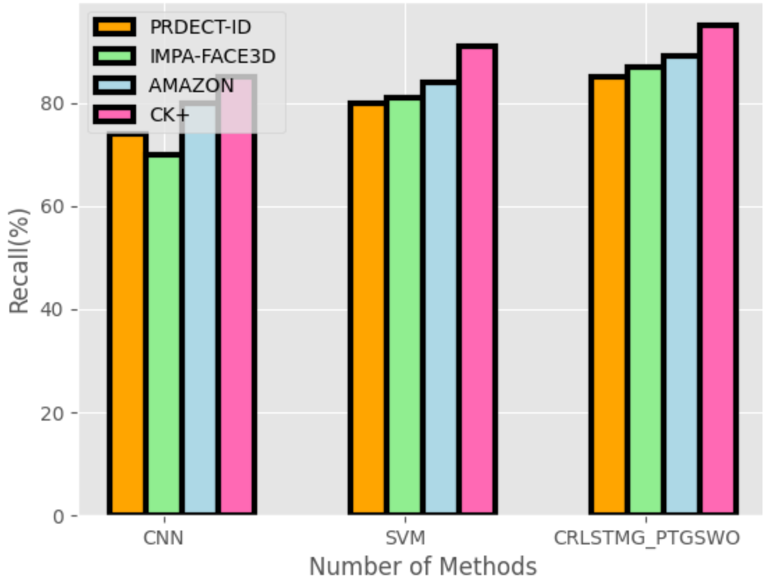

Figure 6. comparison of RECALL

The RECALL analysis is displayed in Figure 6. Here, the proposed technique achieved 85% RECALL, 74% existing CNN, and 80% SVM for the PRDECT-ID dataset; for the IMPA-FACE3D , the proposed technique achieved 87% RECALL , 70% existing CNN, and 81% SVM; for the AMAZON Dataset, the proposed technique achieved 89% RECALL , 80% existing CNN, and 84% SVM, the proposed technique attained 95% RECALL , 81% existing CNN, and 91% SVM for CK+ dataset.

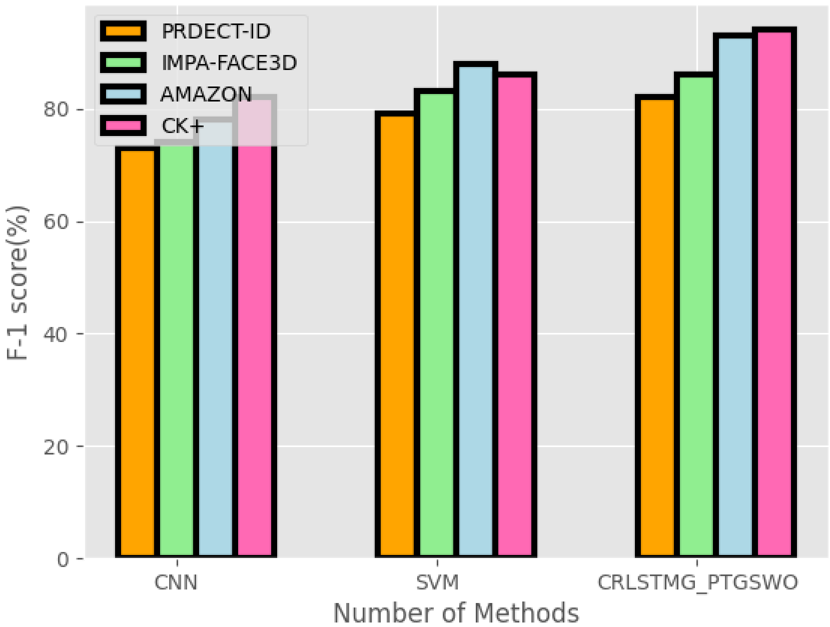

Figure 7. comparison of F-1 SCORE

Figure 7 shows analysis in F-1 SCORE. Here proposed technique F-1 SCORE of 82%, existing CNN 73%, SVM attained 79% for PRDECT-ID dataset; for IMPA-FACE3D proposed technique F-1 SCORE of 86%, existing CNN 74%, SVM 83%; proposed technique F-1 SCORE of 93%, existing CNN 78%, SVM 88% for AMAZON Dataset; for CK+ proposed technique F-1 SCORE of 94%, existing CNN 82%, SVM 86%.

DISCUSSION

We have separated our answers into two categories: affirmative and negative. A positive reaction consists of all pleasant and unexpected feelings, whereas a negative reaction consists of both angry and depressed expressions. Since neutral emotions are neither a good nor a negative response, they have not been taken into account when calculating satisfaction level. Every emotion's count is kept in an array. Following that, the absolute difference between a customer's positive and negative responses was used to calculate their cumulative responses. Four categories are used to categorise satisfaction levels, and the calculated response value indicates which category a given satisfaction level fall into. Thirty of the forty clients that used the suggested model for recommendation purposes were happy with the advice that was delivered. The customer's expression or facial feature was identified and considered when making recommendations.

CONCLUSION

By utilising a meta-heuristic deep learning model for emotion recognition, this study offers a fresh approach to online product-based consumer satisfaction analysis. Customers' online product reviews are gathered here, and the input is then processed for noise reduction, normalisation, and missing value removal. After that, a particle transfer graph swarm wolf optimisation model is used for classification and convolutional regressive LSTM Gaussian model for data feature extraction. The classified output shows the detected emotion from the customer review together with an evaluation of their level of satisfaction. The model evaluation is used to confirm the model's accuracy. Once the classification model is created, the user's consciousness can be removed from the process of classifying their level of happiness by using only the data related to age, gender, and facial expression. Our research will undoubtedly lessen consumers' uncertainties while making smartphone purchases. Our research offers valuable insights for consumers and retailers alike. We attempted to provide an overview of consumer satisfaction for the top five smart phone brands worldwide in our analysis. In light of the pricing issue, a cross-brand comparison of customer happiness is displayed. Furthermore, we have quantified the effects of various smartphone features or traits on customer happiness, which will help product development businesses create strategies that are targeted at the market.

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