A Nano Scale Machine Learning Assisted Natural Language Processing Framework for Sentiment Classification in Smart System Platform

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The study of commercial pages to evaluate the goods or services of a web-based company is a key task for product search, product reviews, digital advertising, and other Smart system tasks. Data libraries have recently offered limited organizational resources or publicly available information, free access. A control and charging process would be enforced for Data libraries to have copyrighted content to use. Electronic commerce allows Data libraries to view protected content and secure copyright holders and Data libraries' rights. This paper presents the Nano Scale Machine learning assisted sentiment classification framework (MLASCF) using Natural Language Processing (NLP) for customer preferences and satisfaction for the products and services on the Smart system website. Using social analytics techniques to analyze the sentiments embedded in customer reviews enables both company product development approaches and individual consumers to compare prices. Nano Scale Machine learning algorithms like Naive Bayes and maximum entropy classifiers have been used on customer review reports accompanied by standard unstructured pre-processing data. The experimental results show a higher accuracy rate of 96.8% with an F-Measure of 92.6 % compared to other existing methods.

Keywords: Natural Language Processing, Smart system, Data libraries, Nano Scale Machine learning, Sentiment analysis.

1. Introduction

Presently, Natural Language Processing relates to Nano Scale Machine learning approaches by utilizing human language structures [1]. NLP's importance is required as an automated framework for intelligent machine interfaces, which has to respond to the opinion of a situation [2]. The capability of a device to access human opinion in Smart system is established by NLP [3]. In sentiment analysis of Smart system, protocols and natural languages are available to do intelligent machine interface using Data libraries [4]. Various researches reported difficulties in NLP applications to implement intelligent machine interface using Data libraries [23]. The language processing procedure is complicated due to the challenging factors like slang of language, regional pronunciation etc. [6]. The NLP helps to overcome uncertainty in text processing [7]. The identification of a sentiment syntactic meaning and parsing are the two significant forms of operation in Data libraries of Smart system [8]. Sources like Nano Scale Machine learning processes, rules-based algorithms are involved in such NLP processes [9].

NLP is related by text analytics that makes enormous quantities of data reported to investigate textual objects and extract text variables from quantitative models and computational approaches [24]. The enormous success of enhancing machine translation of sentiment analysis activities minimizes the network technological demands of the database scheme [11].

The language translation has been accomplished using the NLP process for review analysis on the –commerce websites using the available Data libraries. In review analysis frameworks, the NLP is being utilized to search, analyze, compare, and rating purposes [12].

Though several learning approaches have been used in the conventional research, Nano Scale Machine learning is considered a superior result for optimizing product search, price analysis, and reviews prediction in the database with more accuracy addressed in this paper [15].

Significant contributions of the paper that includes:

1) Designing an MLASCF for perfect sentiment analysis using NLP for motivating the proper preferences in Smart system Websites.
2) Analyze social Smart system sentiments embedded in customer reviews and company development approaches and individual consumers to compare prices [10].
3) Investigate the model using Nano Scale Machine learning algorithms like Naive Bayes and maximum entropy classifiers on customer review reports.

The rest of the paper is organized as follows: Section 2 Describes the related works. Section 3 explores the Nano Scale Machine learning assisted sentiment classification framework (MLASCF). Section 4 elaborates on the results and discussion based on an analysis in section 3. The section-5 concludes the research with future perspectives.

2. Background study

This section discusses several works that have been carried out by several researchers. The Authors in [13] reported strengthening testing unit classification (STUC) to raise more questions when a customer joins a summary. The program wants to restrict the options in which an individual has consumed. The research work in [14] is mainly focused on the problems faced by the researchers, in which there is the use of multi deep neural network (MDNN) models to bypass the traditional function architecture used in Dialog Systems to manage text in appropriation between natural language user queries and organized database entries. In this modern digital library management area, the problem of follow-up clarity resides with potential characteristics of book that has been taken for analysis [5]; for instance, the user utilizes a set of books and the percentage of digital content based on structured text has been calculated with less accuracy is described in [25].

The authors in [16] discussed Deep Neural Belief Networks (DNBN) to grasp the natural language problems and introduce three algorithms. A greedy layer pre-training process, which uses an effective learning algorithm named Contrastive Divergence, has largely stimulated the latest growth of activities in this field. It allows DBN to learn from unlabeled data where multilayer generative architecture and the features found by the algorithm are used to configure a fine-tuned nerve supply network by the back-propagation algorithm.

A DBN-initialized neural network works with the Support Vector Machine algorithm for enhancing the text classification and maximum entropy [17]. The basic SVM-based model has a call-routing accuracy that compares to the best of the other models. Nonetheless, SVM offers significant advantages by utilizing additional unlabeled data for SVM pre-training and integrating SVM-based, experienced features. Various recently published experiments spanning from visual classification and speech recognition to audio processing have been carried out on SVM apps for many problems [18].

In [19], Authors Cumulative neural network models (CNN) have rendered significant accomplishments for multiple linguistic activities in the analysis of natural languages due to the latest gains made in deep learning. This rapid growth, however, presents enormous challenges as well. The fuzzy design of a neural network model contributes to complicated control structures and processes which are challenging to understand.

Implementing a visualization method enables the user to interrogate the model by disturbing data, internal state, and observing changes in other sections of the pipeline via versatile integration of the visualization feature with the underlying model [20]. An illustration of how an interference-led question may help domain experts to determine the possible shortcomings of a concept that has been discussed with the inner condition of shape model.

In [21], the authors suggested NLP problems such as language comprehension, extraction in text-based information, and text or speech creation. It is important to analyses the syntactical constructs of the sentences before successfully solving several of these issues. Syntactic parsing is the duty to construct a syntactic parsing tree over a sentence that defines the sentence structure. As part of several language implementations, parse trees are used by the authors.

In this article, MLASCF using NLP is introduced to address common issues to minimize the transfer learning methods to resolve critical issues relevant to sentiment analysis. The precision with state-of-the-art approach achieves a positive performance in addressing fundamental Smart system analysis using the digital library and in general sentiment analysis activities brief explanation has been discussed as follows,

3. Nano Scale Machine learning Assisted Sentiment Classification Framework (MLASCF) Using Natural Language Processing (NLP)

MLASCF comprises three units for sentiment analysis: data collection, analysis, and gather sentiment information. The data collection unit consists of a database engine that extracts digital library data from the Smart system website for language translation using NLP. The organized management framework is the concern of MLASCF that handles multiple data samples for the transition of actual language to the device language for screening review data. The user interface module includes machine interfaces for the management that helps to maintain functions, as shown in Figure.1.

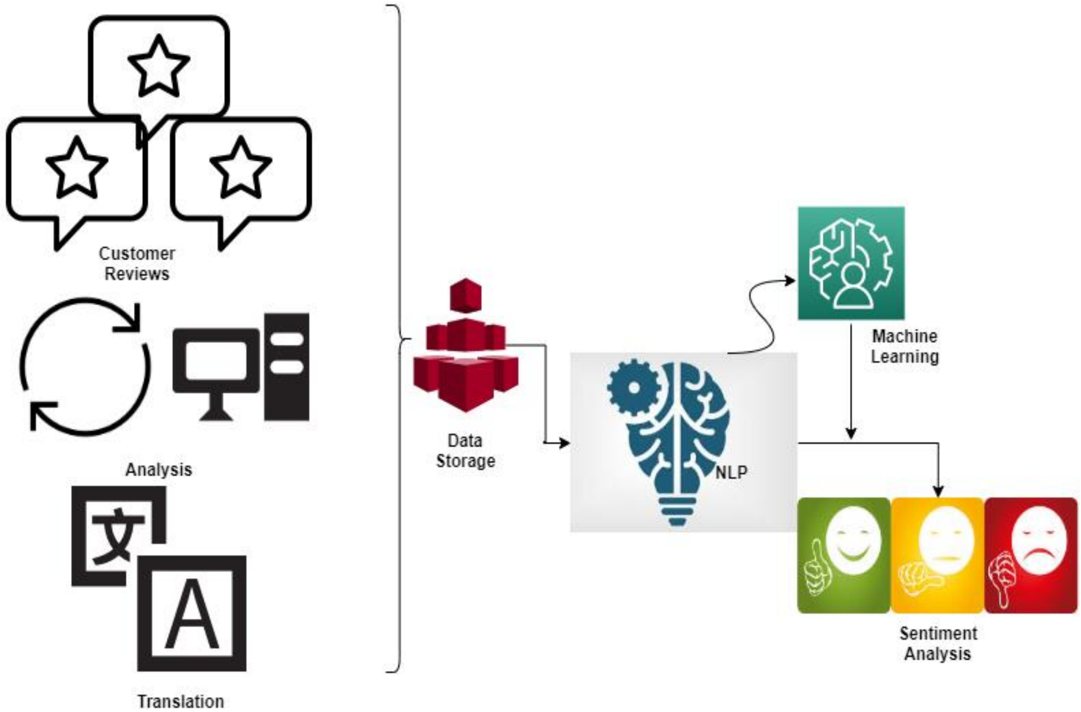

Figure.1. Process Schematic of MLASCF

The Language translation unit converts the review into the interfacing device language. It has been supported by automated spell checker adjustment, which helps analyzer can show the revision of the text performance according to their interpretation. This module utilizes an open platform. For the translation uses based on encoder-decoder model of Nano Scale Machine learning and the new computer translation sentiment analysis approach. This segment introduces more analyzing states to control the grammatical conditions on a finite state of operational search. Such states are useful in interpreting invalid performance terms and offering valuable tips for adequately preparing storage networks. MLASCF has been denied the irrelevant consumer review entries by regretting them. It constructs a regression mechanism at the translation process to determine the consumer inputs and information in the sample dataset. This increases MLASCF performance by using inquiries for storage clarification and data collection. MLASCF converts natural language to support context information, meaning nature to increase machine device interaction quality. The detailed modeling data with a procedural perspective are given in detail as below.

3.1 Modeling of MLASCF

The first process is to create a recurrent framework for the conversion from natural to device language. The storage network essentially balances natural language input as a sequence of terms (A(t), B(t), C(t), Ls(rt-1)) in the encoder unit. The storage network transforms into the decoder unit (Ps, Pj, P0, K(t-1) and initiates to transform natural language into the desired form after all the Data libraries of Smart system inputs have been processed. The reason for the transformation of the storage network to device language translation is given below in the Figure.2.

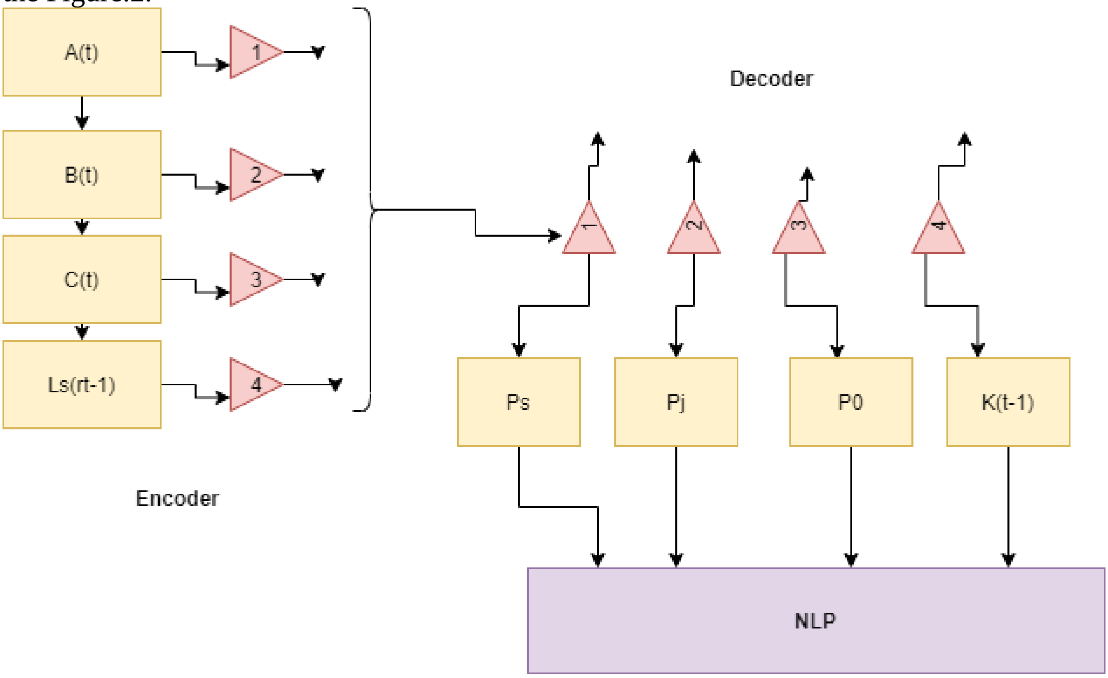

Figure. 2. Encoder-Decoder Modeling

i) Encoder-Decoder Model

The encoder-decoder unit has been targeted to accept and investigate the most relevant and appropriate storage data until the second process unit decoding gets completed. The neglecting factor behind the unwanted semantic features in the Smart system digital library's review languages is suggested to connect with the actual sentiment words to the target natural language's grammatical nature. A collection of correlation is determined using the mapping target encoder and decoder unit.

By integrating the language of an encoder's actual text outputs, strategies are incorporated into a storage network to the encoder-decoder unit. A closed structure is created for translation from the natural langue, as shown in Figure 2. The storage unit comprises data samples from the digital library database of Smart system that embraces natural language sentiments in the encoder as inputs. Throughout the term, depending on the previous outputs, the storage unit is updated and the neglecting recommendation as in Equation (1)-(3)

$$A_t = \in_s (P_s + k_{t-1} + L_s r_{t-1} + t_s) \quad (1)$$

$$B_t = \in_s (P_j + k_{t-1} + L_s r_{t-1} + t_j) \quad (2)$$

$$C_t = \in_s (P_O + k_{t-1} + t_O) \quad (3)$$

Where, A_t, B_t, C_t is the translation time of each sentiment in natural language processing, $\in_s$ is the scaling ratio, $P_s, P_{j,} P_O$ are the input of the storage unit, r is the lack of knowledge for each processing ratio, L_s, L_s is the language acceptance ratio, k_{t-1} is the actual processing rate of true factor ratio, t_s, t, t_O is the distance of each unit. The factor split output operation is explained in as in Equation (4) and (5)

$$t_s = A_t \aleph k_{t-1} + P_j \aleph \in_s (P_j + P_s + L_s r_{t-1} + t_s) \tag{4}$$

$$k_{t-1} = P_O \aleph) \qquad \in_s \tag{5}$$

Here $\aleph$ indicates the process of factor wise spatial unit in language transition, A_t is the translation time of each sentiment in natural language processing. k_{t-1} is the distance processing rate between each text, $t_s, L_s r_{t-1}$ the distance of each network, $P_j + P_s, P_O$ memory in the digital library database. In the decoder, there are erroneous output terms focused primarily on longer-term addition. The decoder at any point and likely acknowledge several rules from long-term dependency. In connection with the current state and last decoder output, the symbols present in a binary vector rule are used to denote the single rule to improve the accuracy rate. In the rule of these, decoder word collection changes are shown in Equation (6)

$$P_t = \in_s (P_x k + t_x) \aleph m \aleph j_1 \ldots \ldots \ldots .. \aleph j_I \tag{6}$$

Here m *and* n denote the long-term dependency on language. $P_x k$ is the time taken for each request, $\in_s$ is the vector, j_I is the scaling vector.

Thus the encoder-decoder unit has been designed effectively with process assumption, and further improvisation is done through the processing model, which is studied and implemented as follows.

ii) Processing Model

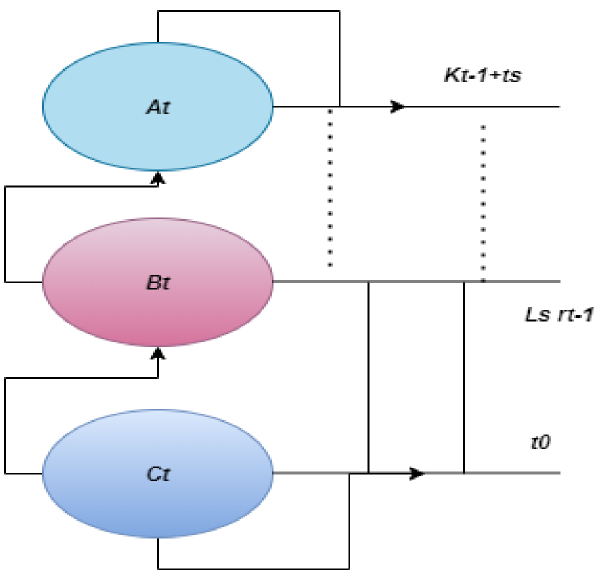

Figure. 3. Storage Unit model

The Product search in the Smart system denial platform is used to access the database scheme by the prediction model's storage unit as shown in the Figure.3 MLASCF gathers entropy statistics for performance selection dependent on the naïve Bayes states that the translation model retains. The main methods used are the threshold approach and the device language process. The 'power approach' actually does not acknowledge that the overall entropy is above the maximum. The second method is the storage unit, utilizing true and false database where the F-measure is optimized as in Equation (7).

Storage language models are used to assign terms to a vector representation and effectively utilize NLP memory networks. Such factors are contained in an embedding price comparison,

$$M \in S^t \times |vz| \tag{7}$$

where vz the language translated and S^t is the semantic component. Typically, this matrix M gathers data and knows the values for the practical sentiment analysis. This tracks data on occurrences and translated into the functional space of the storage unit as for text fragments as shown in Equation (8)

$$x_i = Mb \in X \tag{8}$$

Here Mb is the binary vector which is zero in all x_i indexes, X is the functional space of the deep memory network, M is the text for sentiment analysis. This decreases a different label before merging with all its neighbours of the same label, and it is given in Equation (9)

$$\Delta(Mb) = X \sum_{b \in m(\hat{x})} 1\{sub(Mb) \in X(Mb)\} \tag{9}$$

Here $\Delta(Mb)$ is the loss, for proposing input $b \in m(\hat{x})$ with labels $X(Mb)$. Sub node sub (Mb) appears in-ground node. The illustration of the node and sub-node of the storage unit for NLP processing is explained in Figure. 4.

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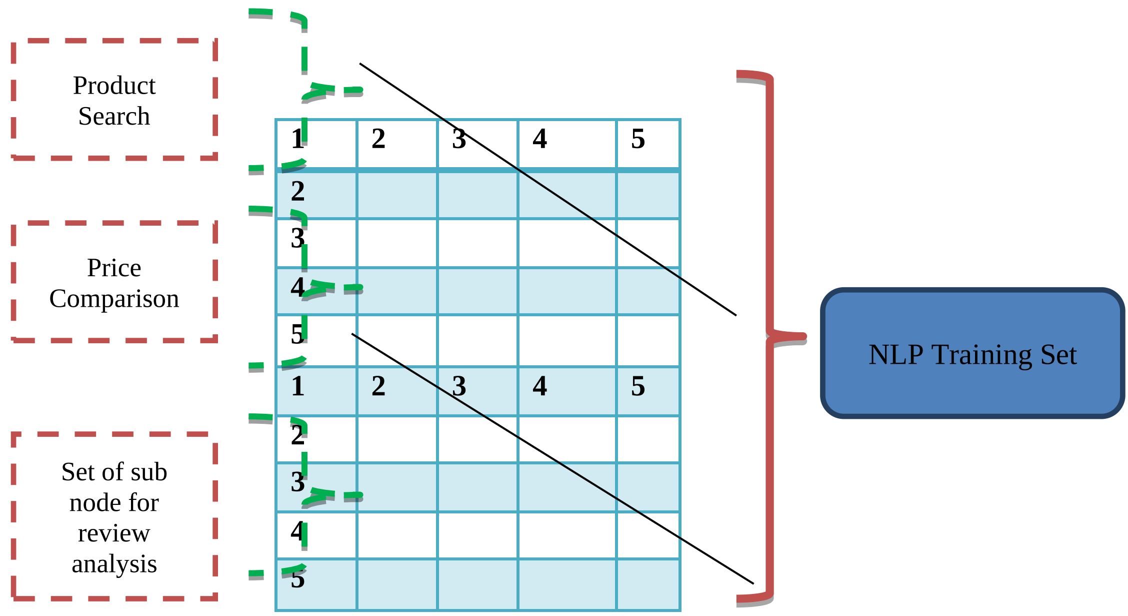


Figure. 4. Storage Unit for NLP Processing

Because of the training set, there is a search for a function in sentiment analysis with small inputs as in Equation (10)

$$g_{\varphi}(y) = (ML(\varphi, y, \hat{x})) \tag{10}$$

Where $\cdot\varphi$ are all required parameters for calculating output value. Here $\varphi, y, \hat{x}$ is a tree value that the tree layout is in the set is $g_{\varphi}(y_j)$For all training instances. The associate margin loss is given by Equation (11)

$$t(ML(\varphi, y, \hat{x}) \geq t(ML(\varphi, y, \hat{x}) + \Delta(ML(\varphi, y, \hat{x}) \quad (11)$$

Here Δ is the margin loss, which includes noise due to external factors. These noises $\varphi, y, \hat{x}$ are generated during sentiment analysis. The training and loss are illustrated in Figure. 5. The sequence-to-sequence learning and its derivatives are widely used for product searching in the price comparison process based on the rating, which helps to reduce the noise factors of the database

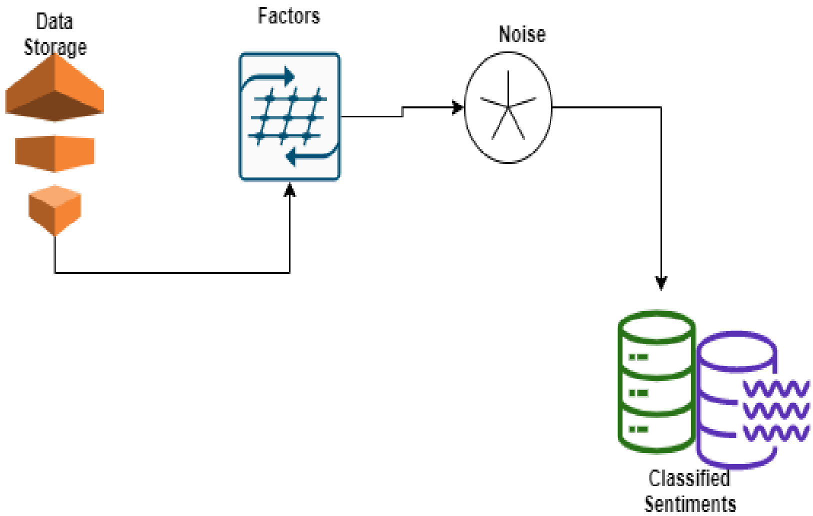


Figure. 5. Noise reduction of MLASCF

The output to pick searches for extending the category of applicants into primary sentiment analysis. The cost function of MLASCF is clearly shown in Equation (12) and (13)

$$C(\varphi) = \frac{1}{M}\sum_{j=1}^{M} X_j(\varphi) + \|\varphi\|^2 \quad (12)$$

$$X_j(\varphi) = MAX(y_j, \hat{x})) + \Delta((ML(\varphi, y, \hat{x})) \quad (13)$$

Here $X_j(\varphi)$ is the function of MLASCF. $\|\varphi\|^2$ is the total time taken for the output processing, $\Delta((ML(\varphi, y, \hat{x}))$ is the training instances, $\frac{1}{M}$ is the scaling parameter. $C(\varphi)$ is the cost function which is reduced using the Equation (12) The outcome that is used to sum all local decisions is as in Equation (14)

$$r\left((\varphi, y_j, x_j)\right) = SD \quad (14)$$

The sample size SD is connected to a discrete model parameter for the created marginal likelihood is given by $r\left((\varphi, y_j, x_j)\right)$ which induces distribution over a decoder composed of the marginal probability of individual data points is shown in Equation (15) and (16)

$$\log(E_r) = \sum_{j=0}^{M} \log((E)) \quad (15)$$

$$l\log(E_r) = \sum_{j=0}^{M} \log((E)) = E_1 + E_2 + E_3 + \cdots \dots \dots \dots .. E_n \quad (16)$$

Where parameters $E_r$and E is the cumulative error vectors to reduce the difference between the predicted and actual parameters with optimized error factor, $\dots \dots \dots \dots .. E_n$.

Thus, the likelihood of sentiment analysis over the digital library of the Smart system websites with MLASCF forwarded as an adverse reconstruction and error and other parametric evaluation has been done for this generative model helps as follows with the analysis model so far developed. Based on the Modelling computation, the experimental results indicate the MLASCF technique is implemented to improve the sentiment analysis on the Smart system paradigm using the digital library data samples by utilizing the Nano Scale Machine learning approach and NLP.

4. Results and Discussions

The proposed model is analyzed using sample datasets gathered from semeval 14 tasks 4 digital library databases [22] for measuring various parameters like accuracy, error rate, F-measure, duration, cost function, and noise in reconstructing the sentiment analysis operation using MLASCF by the likelihood of data point in the sample

The sample data is an additional noise with an approximated likelihood point counted as a reconstructing parameter for the proposed model. The Error rate of MLASCF is shown below in Figure .6.

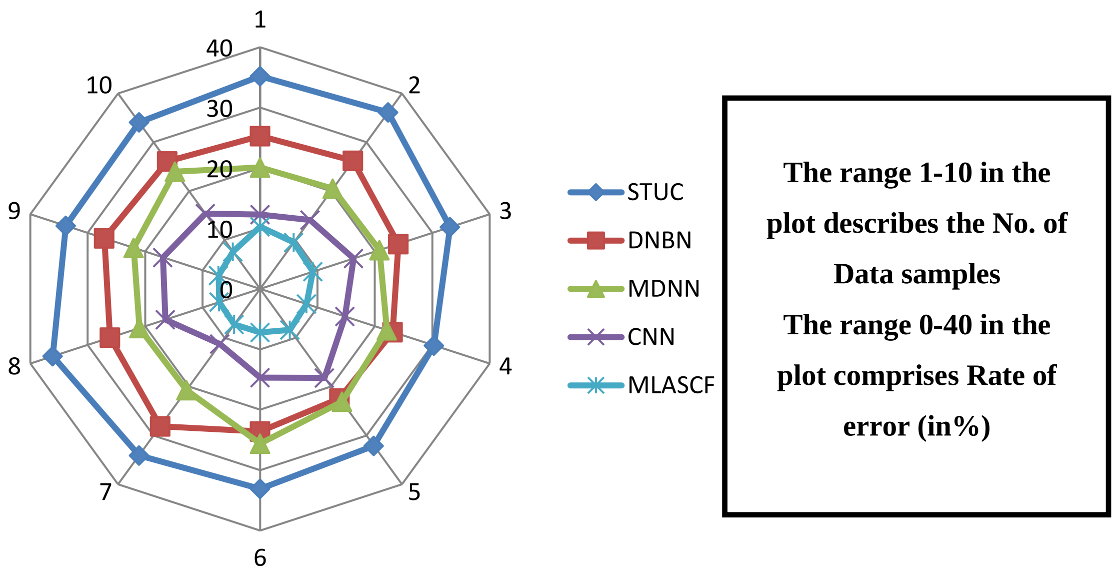
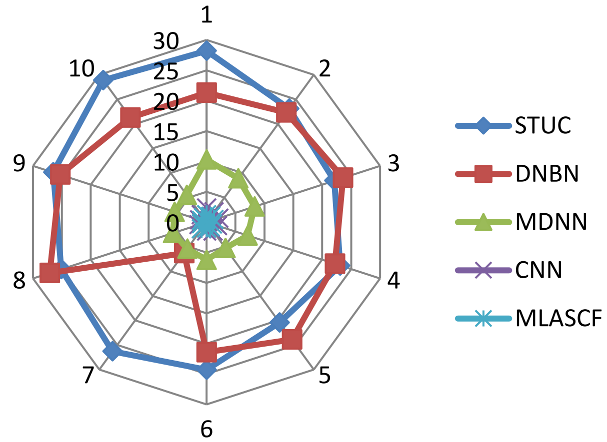


Figure. 6. Error Rate analysis

The error rate of MLASCF using NLP is shown in Figure .6. Consequently, the MLASCF use the instruction in two stages, namely reconstructing and modeling. For that, a set of error calculation is done by analyzing the encoding and decoding stages. Since the error rate computation is shown in Equation (16), the likelihood given in the samples for reconstructing the sentiment analyzing model helps to reduce the error occurrence for both the stages.

Throughout the sentiment analysis framework, to obtain a minimum operation duration, the

MLASCF upgrades the encoder and decoder units. In the analysis process, parameters are modified to distinguish the self-encoder from the distributed vector. Along with this, the proposed MLASCF updates similar parameters to create search engine vectors. The duration analysis phase is clearly shown in Figure. 7. Since it takes simultaneous encoding and decoding options, it puts an emergence of sentiment analysis with minimum duration.



The range 1-10 in the plot describes the No. of Data samples
The range 0-30 in the plot comprises Time duration (in%)

Figure. 7. Duration Analysis

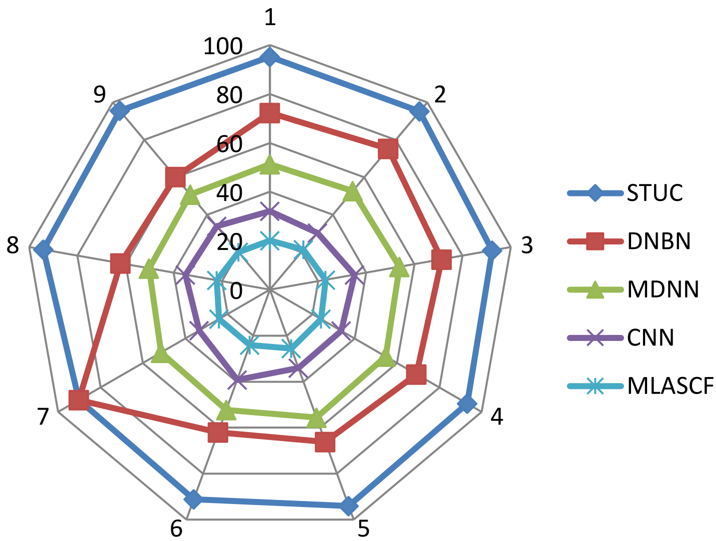
An encoder is implemented for the noise function with multilayer perception (MLP) with the variation approximate expected to be under the diagonal mean and variance as in Equation (11). The number of digital library Smart system samples is compared with conventional methods, shown in table.1.

Table.1. numerical analysis for Noise Function (in %)

No. of Data Samples	STUC	DNBN	MDNN	CNN	MLASCF
10	22.1	19.2	12.2	10.9	5.1
20	21.3	18.3	11.5	9.9	5.1
30	25.6	18.9	11.6	8.8	4.2
40	26.5	18.4	13.6	8.9	4.6
50	21.4	17.6	12.3	8.6	3.2
60	23.6	17.9	11.8	9.2	2.5
70	21.3	16.5	11.1	8.4	2.2
80	24.6	16.4	12.3	8.1	2.1
90	29.6	16.6	11.6	8.4	1.9
100	21.6	16.2	11.5	8.2	1.2

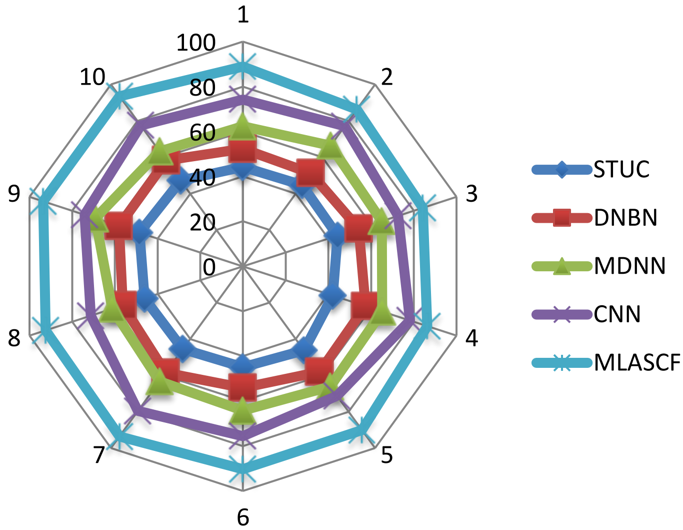
To hold many sets of sentiment frames simultaneously, sequence-to-sequence learning and its derivatives are widely used for product searching in the inference process based on

diagonal mean and variance, which reduces the noise function in accordance with the noise values which are taken for analysis with the corresponding estimation.
Many samples have been taken to cost function measurement, and the procedure has been adopted to evaluate the models in terms of different perspectives of sentiments in the digital library dataset. The evaluation is performed using the MLASCF cost function as shown in Equation (14)
The average cost estimating function based on the number of Smart system digital library samples is shown in Figure .8.



The range 1-10 in the plot describes the No. of Data samples
The range 0-100 in the plot comprises Cost Function (in%)

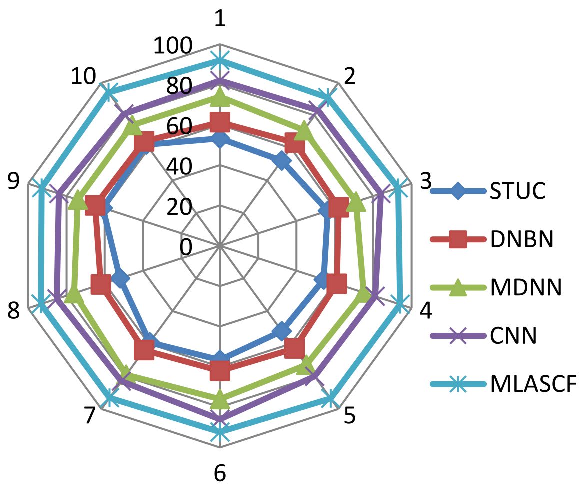
Figure. 8. Cost Function analysis
For a defined distribution of sentiment frames, the encoder unit transforms the data distribution designed for both the variance and mean to minimize the difference between the predicted and actual sentiments with optimized search time and the comparison time, which reduces the cost function.



The range 1-10 in the plot describes the No. of Data samples
The range 0-100 in the plot comprises Rate of Accuracy (in%)

Figure. 8. Accuracy Rate analysis

MLASCF with NLP may decline irrelevant consumer reviews by neglecting a rejection mechanism at the top of the language-translation and product search process to determine the accuracy between dataset inputs and information gathered as in Equation (6) by MLASCF. Sentiment choices are taken into account of the translation for dataset search, compare, and rating phrases. Meanwhile, the actual samples and the false samples are differentiated depending upon the sentiment recommendation comments with accuracy, as shown in figure 8.



The range 1-10 in the plot describes the No. of Data samples
The range 0-100 in the plot comprises Rate of F-Measure (in%)

Figure. 9. F-Measure determination analysis

MLASCF converts sentiments to natural language to support information analysis, meaning that the nature of inquiries increases the device interaction. The power approach does not acknowledge that the overall entropy is above the maximum of classification using both naive Bayes and maximum entropy, utilizing the true and false database of the Smart system. The F-measure is optimized as in Equation (7). As a virtual sentiment analysis framework, the samples' overall contribution indicates input text translation and analysis. The unrelated datasets are optimized with a 96.8 % accuracy ratio. Based on the statistical analysis, it is possible to access the database with an F-measure of 92.6 %. Thus, MLASCF using the NLP approach helps to optimize of sentiment analysis effectively.
The results regarding accuracy, F-measure, error rate and the duration show the effectiveness of the proposed MLASCF methods. The proposed method suits the idea of sentiment analysis using NLP with proper experimental studies.

5. Conclusion

This paper explores the MLASCF which uses the encoder-decoder unit, with a sample dataset as the input unit, and introduces the search, compare, and rate process parameterization. MLASCF technique is implemented to improve the storage digital library network of Smart system to ignore unauthorized contents of the objective database. Further, the MLASCF technique works well with the social analytics techniques to analyze the sentiments embedded in customer reviews, enable both company product development approaches and individual consumers to compare prices. It has been utilized Nano Scale Machine learning algorithms like Naive Bayes and maximum entropy classifiers on customer review reports accompanied by standard unstructured pre-processing data with an accuracy rate of 96.8%and F-measure of 92.6%. The future work can be extended by reducing operational time and cost by achieving high-performance accuracy.

References

1. Saura, J. R. (2020). Using Data Sciences in Digital Marketing: Framework, methods, and performance metrics. Journal of Innovation & Knowledge.
2. Deena, G., Raja, K., PK, N. B., & Kannan, K. (2020). Developing the Assessment Questions Automatically to Determine the Cognitive Level of the E-Learner Using NLP Techniques. International Journal of Service Science, Management, Engineering, and Technology (IJSSMET), 11(2), 95-110.
3. Zdravevski, E., Lameski, P., Trajkovik, V., Chorbev, I., Goleva, R., Pombo, N., & Garcia, N. M. (2019). Automation in systematic, scoping and rapid reviews by an NLP toolkit: a case study in enhanced living environments. In Enhanced Living Environments (pp. 1-18). Springer, Cham.
4. Ferilli, S., & Angelastro, S. (2019, January). Towards a process mining approach to grammar induction for Data libraries. In Italian Research Conference on Data libraries (pp. 291-303). Springer, Cham.
5. Idowu, A. O., & Eiriemiokhale (CLN), K. A. (2020). Availability and Awareness of Electronic Databases for Teaching and Research by Lecturers in Public Universities in South-West, Nigeria. Indian Journal of Information Sources and Services, 10(1), 27–35.
6. Cobos, R., Jurado, F., & Blázquez-Herranz, A. (2019). A Content Analysis System that supports

Sentiment Analysis for Subjectivity and Polarity detection in Online Courses. IEEE Revista Iberoamericana de Tecnologías Del Aprendizaje, 14(4), 177-187.
7. Rameshbhai, C. J., & Paulose, J. (2019). Opinion mining on newspaper headlines using SVM and NLP. International Journal of Electrical & Computer Engineering (2088-8708), 9(3).
8. Goel, P., Goel, V., & Gupta, A. K. (2020). Multilingual Data Analysis to Classify Sentiment Analysis for Tweets Using NLP and Classification Algorithm. In Advances in Data and Information Sciences (pp. 271-280). Springer, Singapore.
9. N, Ravi, and Swanand Kulkarni. 2023. “Smart Ways to Catch the Abutment DRCs at IP Level”. Journal of VLSI Circuits and Systems 6 (1):51-54. https://doi.org/10.31838/jvcs/06.01.08.
10. Nikhita, N. S., Hyndavi, V., & Trupthi, M. (2019, March). Detection of Inappropriate Anonymous Comments Using NLP and Sentiment Analysis. In International Conference on E-Business and Telecommunications (pp. 131-138). Springer, Cham.
11. Sinha, S., & Narayanan, R. S. A (2023). Novel Hybrid Lexicon Ensemble Learning Model for Sentiment Classification of Consumer Reviews. Journal of Internet Services and Information Security, 13(3), 16-30.
12. Dridi, A., Atzeni, M., & Recupero, D. R. (2019). FineNews: fine-grained semantic sentiment analysis on financial microblogs and news. International Journal of Nano Scale Machine learning and Cybernetics, 10(8), 2199-2207.
13. Ramanathan, V., & Meyyappan, T. (2019). Prediction of Individual's Character in Social Media Using Contextual Semantic Sentiment Analysis. Mobile Networks and Applications, 24(6), 1763-1777.
14. Naseem, U., Razzak, I., Musial, K., & Imran, M. (2020). Transformer based deep intelligent contextual embedding for twitter sentiment analysis. Future Generation Computer Systems, 113, 58-69.
15. Giménez, M., Palanca, J., & Botti, V. (2020). Semantic-based padding in convolutional neural networks for improving the performance in natural language processing. A case of study in sentiment analysis. Neurocomputing, 378, 315-323.
16. Yolvi, J.O.F., Walter, G.G., Luis, A.V.F., Segundo P.V.R., Huguette, F.D.Z., Jackeline R.H.F., & Marco, A.A.B. (2023). A Novel Approach to Predict the Early Childhood Special Education Learning Skills of Autistic Children Using Ensemble Machine Learning. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 14(2), 59-65.
17. Janda, H. K., Pawar, A., Du, S., & Mago, V. (2019). Syntactic, Semantic and Sentiment Analysis: The Joint Effect on Automated Essay Evaluation. IEEE Access, 7, 108486-108503.
18. Priyantina, R., & Sarno, R. (2019). Sentiment Analysis of Hotel Reviews Using Latent Dirichlet Allocation, Semantic Similarity and LSTM. International Journal of Intelligent Engineering and Systems, 12(4), 142-155.
19. Shams, M., Khoshavi, N., & Baraani-Dastjerdi, A. (2020). LISA: Language-Independent Method for Aspect-Based Sentiment Analysis. IEEE Access, 8, 31034-31044.
20. Shakeel, M. H., Faizullah, S., Alghamidi, T., & Khan, I. (2020, February). Language Independent Sentiment Analysis. In 2019 International Conference on Advances in the Emerging Computing Technologies (AECT) (pp. 1-5). IEEE.
21. Liu, N., Shen, B., Zhang, Z., Zhang, Z., & Mi, K. (2019). Attention-based Sentiment Reasoner for aspect-based sentiment analysis. Human-centric Computing and Information Sciences, 9(1), 35.
22. Emadi, M., & Rahgozar, M. (2020). Twitter sentiment analysis using fuzzy integral classifier fusion. Journal of Information Science, 46(2), 226-242.
23. http://alt.qcri.org/semeval2014/task4/index.php?id=data-and-tools
24. Van Der Mheen, M., Dijkstra, H. A., Gozolchiani, A., Den Toom, M., Feng, Q., Kurths, J., & Hernandez–Garcia, E. (2013). Interaction network based early warning indicators for the Atlantic MOC collapse. Geophysical Research Letters, 40(11), 2714-2719.

25. Rajput, A. (2020). Natural Language Processing, Sentiment Analysis, and Clinical Analytics. In Innovation in Health Informatics (pp. 79-97). Academic Press.
26. Gan, C., Wang, L., Zhang, Z., & Wang, Z. (2020). Sparse attention based separable dilated convolutional neural network for targeted sentiment analysis. Knowledge-Based Systems, 188, 104827.