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# Supervised Learning Technique for Recommendation Systems based on Amazon Product Reviews

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## ABSTRACT

Due to the rapid growth of internet of things (IoT) and artificial intelligence technology, e-commerce is now available worldwide. In order to give customers additional options for buying at their homes, e-commerce businesses offered an infinite number of products. Despite its advantages, shopping presents considerable problems in terms of selecting the best and most appropriate products. To remedy this, researchers created recommendation systems (RS) for customers that promote appropriate products based on their preferences and ratings. To lower the erroneous rate in product selections, we created an intellectual supervised learning model with a recommendation forecaster in this study. The convolutional neural network (CNN) is developed as the automatic feature extractor of recommendation system in order to produce accurate selections and the data is feed-forwarded into extreme learning machine (ELM) to forecast the upcoming products ahead based on the Amazon reviews and twitter emoji user replies. The proposed CNN-ELM recommendation system outperformed than traditional learning models in terms of accuracy, sensitivity, specificity, precision and F1-score metrics. In an average of 96.5% exactness achieved by CNN+ELM predictor.

**Keywords: -** Recommendation systems, machine learning, Amazon reviews, sentimental analysis, hybrid algorithms.

## I. INTRODUCTION

Information is wealth said by a philosopher which comes true in recent digital environment especially in online market. The rising digital commerce sector, along with tighter operating budgets, allows e-commerce businesses to make informed decisions about which technologies to invest in and which to avoid called Recommendation system (RS) [1]. RS become user-friendly to customers in terms of recommending their favourites new products automatically based on their perceptions and reviews. The most popular e-commerce market engines are “Amazon, flip kart, e-bay, Snapdeal, Alibaba”, etc. for recommending the new products from portable to high-end computers [2]. RS plays a vital role in online market in terms of increases the product revenue. The market for recommendation engines was worth USD 2.12 billion in 2020, and it is predicted to grow to USD 15.13 billion by 2026, with a CAGR of 37.46 percent between 2021 and 2026 [3]. Today, RSs are used in many computers’ science companies in such as “Google, Twitter, LinkedIn, and Netflix” [4].

Fig. 1 Shows the recommendation system growth as per the global survey [5]. With the expanding amount of information available on the internet and a considerable increase in the number of users, it is becoming increasingly important for businesses to search, map, and give relevant information based on their preferences and tastes that become very challenging nowadays. Customers are further confused by differing perspectives about the same product on the one hand, and vague reviews on the other, making it more difficult for them to make the best decision. The requirement to analyse these contents appears to be critical for all e-commerce enterprises in this case. These include producing high-quality recommendations, acting on many recommendations per second for multiple people and entities, and attaining high coverage in the face of data scarcity.


Fig. 1 Recommendation system growth as per global survey [5]

Most standard recommendation frameworks are based on three distinct categories content-based model, collaborative model, or hybrid filtering model. In the first model, RS created based on people likes on search and recommends other relevant products similar to their views [6]. Collaborative model suggest the new products based on the other customers likes and opinions [7]. Hybrid model combines both former and latter method [8-10]. A. Noor et al. [11] goes over the various forms of recommendation algorithms.

The most common recommender filtering technique, according to Abien Fred M. Agarap et al. [12], is collaborative filtering; however, in a content-based recommender system, users' preferences and choices are provided through their linked points. In order to generate relevant suggestions, CF collects user ratings for objects in a certain domain and calculates similarities between users or items. The challenges on these standard models are (i) false rate is high (ii) computational complexity (iii) complex in handling big-data. To overcome this, machine learning approaches have gained popularity in semantic and review analysis in recent years because to their simplicity and accuracy. Yuniarta Basani et al, detailed the use of supervised and unsupervised learning modules in recommendation systems. The author identified that decision tree and Bayesian classifiers are widely adopted in the RS recently [13].

### *A. Significant Contributions*

In this study, we created a new recommendation system for e-commerce products named "convolution-based Extreme learning machine" (CNN-ELM), which is similar to the hybrid RS technique.

(i) We characterized various categories of product reviews such as "text-based comments, sentiments, opinions, and emoji", to make a novel database for recommendation systems.

(ii) In terms of different characteristics, the raw data is kept as an unstructured database, demanding the use of an effective feature extractor. To address this, we had been using a convolutional neural network [14] as the feature extractor in order to improve the effectiveness of our recommendation system and get the best results in proposing new items to clients.

(iii) Next, developed the extreme learning machine algorithm for identifying the best new products based on the created RS database. The primary purpose of this ELM model is to minimize the computational complexity of traditional RS without violating the performance.

(iv) These feature extractor and forecasting modules are developed in Python environment and experimentally verified with real-time amazon dataset.

(v) The proposed hybrid recommendation system is associated with traditional collaborative model and other supervised learning models "SVM, decision tree, MLP, RF", for validating the results.

### *B. Outline*

The manuscript organization as follows: relevant works are discussed in section II, Database creation and feature pre-processing is described in Section III, ELM overview and CNN-ELM RS model is elaborated in Section IV and followed by experimental setup in Section V. Evaluation results are detailed with respective bar charts and discussed in Section VI. Limitations and future scope is described under conclusion in section VII.

## II. RELATED WORKS

J. Li et al. in (2007) have suggested a CF based recommendation approach in which hotel feature matrix by polarity identification is achieved using opinion-based sentiment analysis. To understand sentiment toward hotel features and guest type profiling, we used a combination of lexical, syntactic, and semantic analysis (solo, family, couple etc). For individualized recommendations, the suggested system recommends hotels based on hotel attributes and guest type created system not only has the ability to manage heterogeneous data utilizing the Hadoop big data platform, but it also uses fuzzy logic to select hotel classes based on guest type [15].

Yefeng Shen et al. in (2017), studied two distinct supervised machine learning techniques, "SVM and Naive Bayes", has been attempted on beauty products from Amazon [16]. The data is collected from SNAP data set because Amazon does not have an API like Twitter to download reviews with. Huang, G.B et al in (2012) developed a sentimental analysis-based RS for five different products recommendations [17]. LDA model to calculate customer preference on book topics and use word2vec to calculate customer preference on book types. In order to forecast rating on books, we take two factors into consideration: similarity of customers and correlation between customers and books. Experiment shows that our hybrid recommendation method based on features performances better in offline bookstore data [18].

Li. R et al in (2010), developed the user-recommender interaction is defined. The recommender system takes the user's request, suggests N things, and records the user's decision. If some of these products appeal to the user, she will choose one to peruse and use the recommender system until none of the suggested items appeal to her. Second, a hybrid recommender system integrating random and k-nearest neighbour algorithms is proposed. Third, in order to evaluate the recommender system, we redefine the recall and diversity measures depending on the new scenario. Experiments on the well-known Movie Lens dataset reveal that hybrid algorithms outperform non-hybrid algorithms [19].

## III. PROPOSED METHODOLOGY

In this paper, we created a new database based on online review "sentiments, opinions and emoji", as a raw data in the unstructured format and then it converted into .csv format. The convolutional-neural network is used to obtain the significant features in terms of "features" which is described below. Then, ELM overview is given with its basic structure and hybrid RS module is elaborated with its algorithm.

### *A. CNN based Feature Extractor*

Convolutional neural networks (CNN) are used to automatically extract, and then extreme learning machine (ELM) is used to further classify opinions. The information is standardized before being applied in two layers for further processing. For bag of sentiments extraction, the word2vec calculation is adopted in the first layer [20]. The Fig. 2 shows the overview of machine learning based RS.

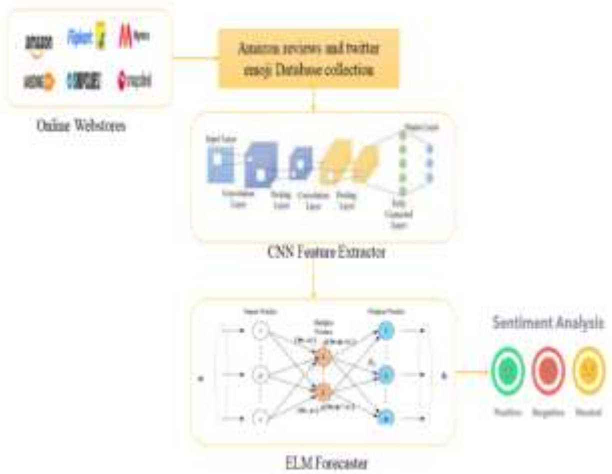


Fig. 2 Overview of the machine learning based RS

### B. *Convolutional Neural Network*

A CNN has several convolutional layers and each convolutional layer may be followed by a pooling layer that determines the average or max of a window of neurons. This layer reduces the complexity of the output feature maps and achieves translation invariance and reduce over-fitting. The last layers of a CNN are the fully connected (FC) or dense layers interconnecting all neurons of previous layers so that complex features extracted by the convolutional layers are globally correlated. In each fully connected layer there are also several kernels. However, in dense layers these kernels are only applied once to the input map. Consequently, dense layers are not computationally intensive since each kernel is only used once. Fig. 3 Illustrates the complete architecture for CNN .The pre-trained vector matrix "Y" is the input to the proposed CNN architecture. Let "K" be the group of input vector matrix in "K" predefined vectors. The input vector matrix of each and every word is given as follows

$$Y_{1:K} = Y_1 \oplus Y_2 \oplus Y_3 \oplus Y_4 \oplus Y_k \quad (1)$$

$\oplus$ Denotes the "concatenation operation". In the first stage, filter layers with dimension of L € $Y_k$ where "Y" is y-dimensional pre-trained vectors and k is size of each filter layers and also the number of vectors in input matrix. The input word matrix is convoluted with filter kernel k to get first set of features.

From the equation (1) spatial features such as edges, corners are captured. The first spatial features which are obtained from equation (2) which is given as

$$A(i) = F(L^* Y_K + O) \quad (2)$$

Where "O" denotes the "bias factors". As the next step, filter "L" is rolled over all the possible combinations of words and different feature vectors are given as

$$A(i) = [A_1, A_2, A_3, A_4, \ldots \ldots A_L] \quad (3)$$

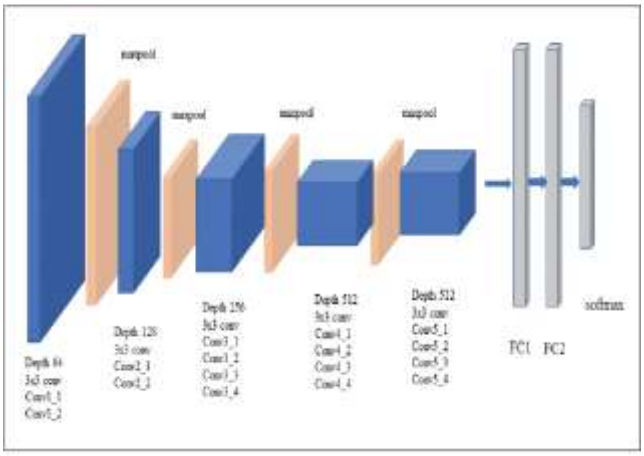


Fig. 3 CNN features extractor for recommendation system

The output feature maps are then fed to pooling layers where pooling layers takes the average value of $A(a_{avg})$ , which is considered to be most important feature with average values as the features equivalent to its particular kernel. This complete cycle is employed for one filter and to extract the feature from max- pooling layer. Multiple filter layer and pooling layers are used to attain the numerous feature maps. The network details are 5-layers of Convolutional layers and 4-layers of Average Pooling layers along Rectified Linear Unit (ReLU) activation unit are used to extract the unknown features from database automatically.

### C. *ELM Recommendation System Products Forecaster*

The "U" neurons in the hidden layer must work with an activation function that is infinitely differentiable (for example, the sigmoid), whereas the output layer's activation function is straight shown in Fig. 4. Hidden layers in Elm should not be tuned by default. In the suggested ELM approach, the hidden layer does not need to be modified. The loads of the hidden layer are assigned at random (counting the bias loads). It is not the case that hidden nodes are insignificant; nonetheless, they do not need to be tweaked, and the parameters of hidden neurons can be randomly given even ahead of time.

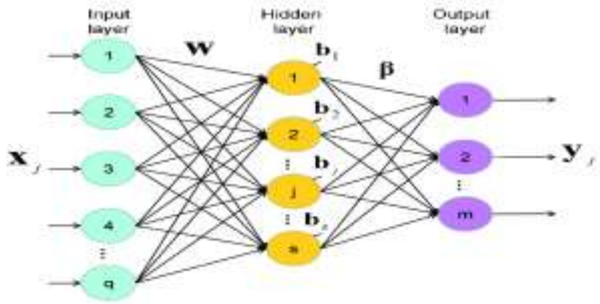

Fig. 4 ELM standard architecture

### D. Mathematical Model of ELM

That is, before taking care of the training set data. For a single-hidden layer ELM, the system yield is given by Eqn.(4)

$$f_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) = h(x)\beta \quad (4)$$

Where x → input, $\beta$ → Output weight vector and it is given as follows as

$$\beta = [\beta_1, \beta_2, \ldots \ldots \ldots \ldots . \beta_L]^T \quad (5)$$

*H(x)* → output hidden layer which is given by the Eqn. (6)

$$h(x) = [h_1(x), h_2(x), \ldots \ldots \ldots \ldots . . h_L(x)] \quad (6)$$

To determine Output vector O which is called as the target vector, the hidden layers are represented by Eqn. (7)

$$H = \begin{bmatrix} h(x_1) \\ h(x_2) \\ \vdots \\ h(x_N) \end{bmatrix} \quad (7)$$

The basic implementation of the ELM uses the minimal non -linear least square methods which are represented in Eqn. (8)

$$\beta' = H^*O = H^T(HH^T)^{-1}O \quad (8)$$

Where H∗ → inverse of H known as Moore−Penrose generalized inverse.

Above eqn can also be given as follows

$$\beta' = H^T(\frac{1}{c}HH^T)^{-1}O \quad (9)$$

Hence the output function can be find by using the above Eqn.

$$f_L(x) = h(x)\beta = h(x)H^T(\frac{1}{c}HH^T)^{-1}O \quad (10)$$

Algorithm1: ELM Prediction steps

***Input:*** Trained dataset with random number of weights and bias values

***Output:*** Predicted Score in terms of Exactness and loss values

1. Initialization of input neurons ‘O’
2. Generate Set of concealed neurons as single layer
3. Softmax function is defined as an activation function
4. Synapses parameters are spawned through Gaussian random method
5. After each iteration concealed matrix are updated
6. The output matrix values are calculated

Final prediction scores

## IV. EXPERIMENTS AND ANALYSIS

The section discusses about dataset descriptions, experimentations, performance metrics and result analysis comparing with other state-of art algorithms.

### A. Curation of datasets

To assess the suggested architecture's efficiency, we examined two separate datasets. The proposed method is put to the test by gathering feedback from a variety of people.

The new structure is examined using the three flexible datasets. Both datasets have a five-class distribution, ranging from 0 to 4 (0-negative, 1-positive,2-neutral, 3- Excellent 4-Good). The table 1 shows the datasets used for the experimentation

The statistics of data are shown in the Table 1. Three kinds of data were utilised to evaluate the suggested design, with the total data being divided into training and testing.

TABLE I
DATASETS USED FOR EXPERIMENTATION

| S.No | Datasets | Number of Data | Training (%): Testing (%) |
|---|---|---|---|
| 01 | Amazon Product Reviews (Text Data) | 5M | 70:30 |
| 02 | Kaggle datasets | 1.8M | 70:30 |
| 03 | Twitter datasets | 1.6M | 70:30 |

### B. Evaluation Setup

The whole experimentation is carried out in the “Intel I7CPU with 2GB NVIDIA GeForce K+10 GPU, 16GB RAM, 3.0 GHZ with 2TB” HDD. The proposed architecture is implemented using TensorFlow 1.8 with Keras API. All the programs are implemented in the anaconda environment with python 3.8 programming.

### C. Performance and Evaluation

With the various datasets obtained, performance indicators such as "accuracy, precision, recall, specificity, F1-score, and specificity" are examined for the proposed framework. The numerical methods for computing performance measurements are shown in the chart below.

TABLE III
ESTIMATION OF PERFORMANCE METRICS USING MATHEMATICAL EXPRESSIONS

| Performance Metrics | Mathematical Expression |
|---|---|
| Accuracy ($A_{cy}$) | $\frac{TP+TN}{TP+TN+FP+FN}$ |
| Sensitivity ($S_{ty}$) or recall | $\frac{TP}{TP+FN}$ x100 |
| Specificity ($S_{cy}$) | $\frac{TN}{TN+FP}$ |
| Precision ($P_n$) | $\frac{TN}{TP+FP}$ |
| F1-Score ($F1_{re}$) | $2.\frac{Precison * Recall}{Precision + Recall}$ |

“TP is True Positive Values, TN is True Negative Values, FP is False Positive and FN is false negative values”.

### D. Results and Discussion

The recommendation system predictor designed to analyse the sentiments, opinions, and emoji features in order to detect the best upcoming products and increases the online stores revenue. The performance parameters are detailed above which is obtained for 30% testing unseen data. In total, three different datasets are used such as “Amazon, Kaggle, and Twitter”, for preparation and evaluation. The below tables and figures are illustrates the obtained results.

TABLE IIIII
PERFORMANCE METRICS FOR DIFFERENT DATASETS

| **Algorithm Details** | **Performance Metrics** | | | | |
|---|---|---|---|---|---|
| | **$A_{cy}$ (%)** | **$S_{ty}$ (%)** | **$S_{cy}$ (%)** | **$P_n$ (%)** | **$F1_{re}$ (%)** |
| Amazon Datasets | 96.5 | 93.8 | 90.2 | 93.2 | 94.5 |
| Kaggle datasets | 96.1 | 93.2 | 90.5 | 92.4 | 93.5 |
| Twitter datasets | 96.4 | 94.2 | 91 | 94.6 | 93.7 |

TABLE IVV
PROPOSED FRAMEWORK PERFORMANCE METRICS EVALUATION FOR AMAZON DATASET

| **Algorithm Details** | **Performance Metrics** | | | | |
|---|---|---|---|---|---|
| | **$A_{cy}$ (%)** | **$S_{ty}$ (%)** | **$S_{cy}$ (%)** | **$P_n$ (%)** | **$F1_{re}$ (%)** |
| CNN | 90.5 | 91.5 | 91 | 90.5 | 91.5 |
| CNN+LSTM | 91.6 | 92 | 91.5 | 91 | 91.4 |
| BIGRU | 92.6 | 93 | 92 | 92.5 | 92.3 |
| ATTENTION BIGRU | 93.1 | 92.4 5 | 93 | 91.8 | 92.7 |
| CNN+ Boosted LSTM | 97.5 | 97 | 96 | 96.2 | 95.5 |

TABLE V
PROPOSED FRAMEWORK PERFORMANCE METRICS EVALUATION FOR KAGGLE DATASET

| **Algorithm Details** | **Performance Metrics** | | | | |
|---|---|---|---|---|---|
| | **$A_{cy}$ (%)** | **$S_{ty}$ (%)** | **$S_{cy}$ (%)** | **$P_n$ (%)** | **($F1_{re}$) (%)** |
| CNN | 90.5 | 91.5 | 91 | 90.5 | 91.5 |
| CNN+LSTM | 91.6 | 92 | 91.5 | 91 | 91.4 |
| BIGRU | 92.6 | 93 | 92 | 92.5 | 92.3 |
| ATTENTION BIGRU | 93.1 | 92.45 | 93 | 91.8 | 92.7 |
| CNN+ Boosted LSTM | 97.5 | 97 | 96 | 96.2 | 95.5 |

TABLE VI
PROPOSED FRAMEWORK PERFORMANCE METRICS EVALUATION FOR TWITTER DATASET

| **Algorithm Details** | **Performance Metrics** | | | | |
|---|---|---|---|---|---|
| | **$A_{cy}$ (%)** | **$S_{ty}$ (%)** | **$S_{cy}$ (%)** | **$P_n$ (%)** | **($F1_{re}$) (%)** |
| CNN | 90.5 | 91.5 | 91 | 90.5 | 91. |
| CNN+LSTM | 91.6 | 92 | 91.5 | 91 | 91.4 |
| BIGRU | 92.6 | 93 | 92 | 92.5 | 92.3 |
| ATTENTION BIGRU | 93.1 | 92.45 | 93 | 91.8 | 92.7 |
| CNN+ Boosted LSTM | 97.5 % | 97% | 96% | 96.2% | 95.5% |

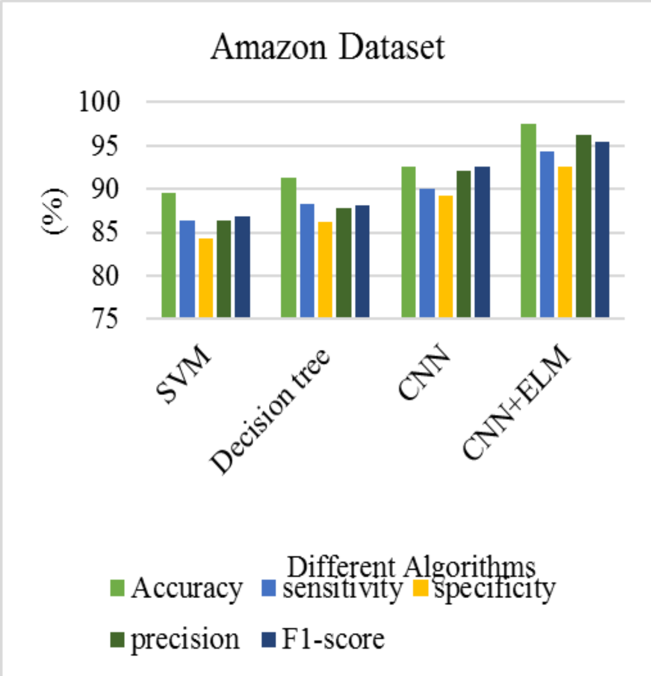


Fig. 5 Performance metrics for Amazon database

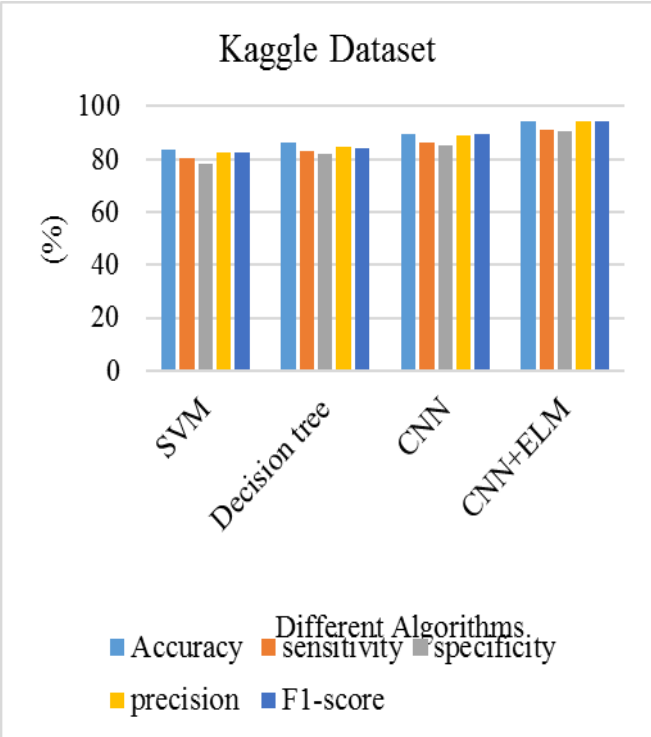


Fig. 6 Performance metrics for Kaggle database

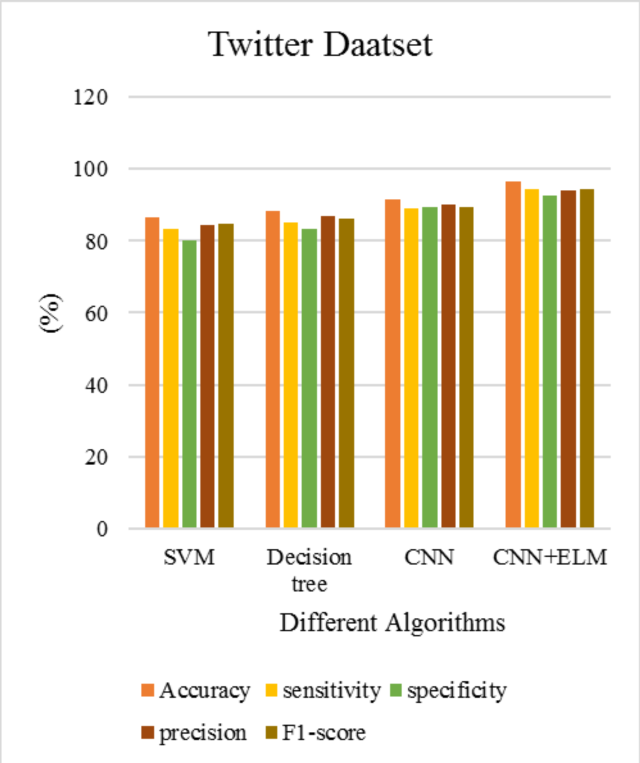


Fig. 7 Performance metrics of twitter dataset

From Table 3, Table 4, Table 5, Figure 5, Fig. 6 and Fig. 7 shows the proposed framework outperformed other existing frameworks in terms of accuracy, sensitivity, specificity and F1-score.

## V. CONCLUSION

Retailers must alter their stores and take their businesses ahead digitally in order to comprehend customers and their need for convenient and consistent shopping experiences. To achieve this, recommendation systems are developed based on the customer's reviews and opinions. Similarly, we developed a new recommendation system called CNN-ELM intellectual learning predictor to identify best products based on amazon reviews and twitter emoji symbols. The proposed machine learning RS is trained and tested with three distinct datasets "Amazon, Kaggle, and Twitter reviews". The proposed CNN-ELM recommendation system outperformed than traditional learning models in terms of accuracy, sensitivity, specificity, precision and F1-score metrics. In an average of 96.5% exactness achieved by CNN+ELM predictor.

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