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Predictive Integrated Convolution Neural Network with Bi LSTM Model for E-Commerce Product Marketing

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Abstract
E-commerce has gradually become one of the most important driving forces for the sustained and vigorous development of country's consumer market. As a result of the rapid development of network and informatization, the application and maturity of technologies like the Internet, terminal equipment, logistics, and payment, and the continuous improvement of people's consumption concepts is growing. The typical marketing methodology does not allow organizations to completely comprehend the needs of their customers. Selling products to customers is the only concern of the e-commerce platforms. They can only concentrate on the product because they don't know what the customer wants. As a result of these limitations, a model for precision marketing that employs integrated convolution neural networks with Bi LSTM (Bidirectional Long Short Term Memory) to create detailed portraits of the target customers. Users' customized items and services are becoming increasingly more dependent on personalized suggestion services as the e-commerce business expands globally. They have the potential to lower the price users pay to gather information while also increasing sales for the company. The use of user reviews to address classic product recommender system research issues has become increasingly common in recent years. Using a convolution and bidirectional long short-term memory hybrid neural network, the review semantics extractor learns how to represent product reviews. Product Recommendations Generator models a user's preference for items based on their prior interactions. In this research a Predictive Integrated Convolution Neural Network with Bi LSTM (PICNN-BiLSTM) is proposed for predictive marketing of e-commerce applications. The proposed model considers Amazon dataset for market prediction and the results represent that the proposed model performance is higher.

Keywords: E-Commerce Platform, Product Recommendation, Convolution Neural Network, Bidirectional Long short-term memory, Product Reviews.

1. Introduction

COVID-19 has had a huge impact on the growth of online shopping, with many countries instituting a stay-at-home order policy for their population. Because of the widespread closure of brick-and-mortar stores due to the threat of infections, customers are increasingly turning to e-commerce retailers to meet their purchasing demands. Textual evaluations and/or ratings are frequent methods used by online merchants to obtain feedback from customers on their products and services [1]. Customers' purchasing decisions are greatly influenced by these internet reviews, and vendors gain valuable information as a result. Customers and sellers can benefit from sentiment analysis, which is a fast and easy way to categories evaluations on online platforms, such as social media [2], because of the vast amount of data they include. As a general rule, sentiment research can be used to improve decision-making processes [3] in a wide range of sectors including enterprises such as banking and stock markets; digital payment systems; retails; and products, among others.

The sentiment ratings have also been researched or attempted to be determined by scholars exploring textual communication sentiment analysis, frequently with scale of 1 to 5 or 10. The use of deep learning in sentiment analysis and product recommendation has increased in recent years, with promising results [4], despite the fact that machine learning is still the most common method used. It has been shown that the more complex and state-of-the-art transformer based pre-trained models like the Bi-directional Encoding Characterizations from Transformers have shown substantially better outcomes in text classifications than popular word embedding techniques like Word2Vec and its derivatives [5]. The use of unsupervised deep learning algorithms has also recently been shown to investigate data augmentation strategies in an effort to increase prediction quality [6]. Using an e-commerce dataset of reviews for clothes, this study intends to use deep learning models to anticipate customer review ratings in order to close the gaps previously observed [7]. To be more specific, this is accomplished by increasing the dataset's variability through pre-processing and data augmentation [8].

Product recommendation model using deep learning is more effective using the long-term short-term memory (LSTM) [8] and the convolution neural networks (CNN) method [9], which are more recent inventions. Input, forget, and output gates are all part of the LSTM gating mechanism, which is an upgraded version of the recurrent neural network (RNN) [10]. It is up to these gates to decide whether or not the prior state's data should be preserved in the present state. Gating helps the LSTM deal with both the problems of long-term data integrity and the vanishing gradients problem faced by traditional RNNs. Recommender systems are beneficial to both service providers and users [11]. Prior studies demonstrate that recommendation engines help consumers to make better decisions, reduce search efforts and find the most suitable prices [12].

A product recommendation system is a software tool designed to generate and provide suggestions for items or content a specific user would like to purchase or engage with. Product recommendation will analyze the existing things more specifically, we focus on fashion products and develop a method that only requires a single input image to return a ranked list of similar-style recommendations. Recommender systems are beneficial to both service providers and users [1]. Prior studies demonstrate that recommendation engines help consumers to make better decisions, reduce search efforts and find the most suitable prices [2].

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Both service providers and end-users benefit from recommendation systems. Recommendations engines have been shown to assist consumers make better selections, save time searching, and locate the best rates [13]. Software designed to produce and deliver ideas for products or content that a specific user might like to purchase or interact with is called a product recommendation system [14]. The implementation of an e-commerce application for the selling of many sorts of products with similar qualities is the subject of this study. Using Transfer Learning and then cosine similarity [15], the deep learning technique provides the most similar products to the user's product choices [16]. Product information and comparable items can be found using the system's features.

It's also true that user preferences shift over time. In order to identify which product is most likely to be sold and which product is least likely to be sold, the organization selling the product must be in profit [17]. We can now avoid this type of misunderstanding and make better selections with the help of recommender systems [18]. There is a long tail phenomenon because preferences differ between the online and physical business. Because a brick-and-mortar store has a finite amount of floor space, it can only display products with high customer ratings or sales [19]. The rest of the merchandise is kept in storage and is only displayed when necessary. Online businesses, on the other hand, are able to display a wide range of products since they have a lot of storage space [20]. Recommendations in a physical store are much simpler because the store has a large number of customers and just those items that the customers prefer are displayed to them. There is no limit to what may be purchased online, however there is a limit to what can be purchased in physical stores [21].

In this research a Predictive Integrated Convolution Neural Network with Bi LSTM (Bidirectional LSTM) is proposed

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for predictive marketing of e-commerce applications. An attention mechanism is used to raise the model's accuracy even further while also reducing the amount of parameters that can be learned. In order to reduce the number of features that need to be entered, a CNN is used in this model [22]. Features extracted from the convolution layers are fed into an LSTM to retrieve reviews and analyze the ratings for better product recommendation. The attention mechanism reduces the amount of parameters that must be memorized during training by using bias realignment over the outputs and weighting highly customized that are significantly connected with classification [23].

The Bi-LSTM neural network consists of LSTM units that operate in both directions to include information from the past and the future [24]. It is possible for Bi-LSTM to learn long-term dependencies without the need to store redundant context information. Due to its good results in sequential modelling challenges, it is commonly employed in product recommendation for online platforms [25]. In contrast to the LSTM network, the Bi-LSTM network comprises two parallel layers that propagate in two directions using forward and reverse passes to capture interdependence in two contexts that is depicted in Figure.

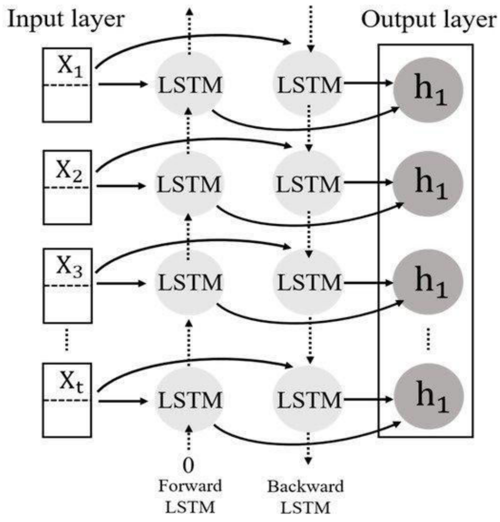

Fig 1: Bi-LSTM Model

Individuals and corporations alike can benefit from the products or services that are recommended. Preferential systems are created to analyze data and find just the most necessary details from huge amounts of data, thereby avoiding the overload of data and making the service as personalized and relevant to the user as possible [26]. User preferences can be predicted by an efficient recommender system by analyzing their own activity, or the behaviour of other users, and using this information to guess the user's interest or preference [27]. Although recommender systems are commonly associated with e-commerce, they have proven effective in a variety of other fields as well.

Recommendation systems are designed to improve the operation of e-commerce systems by making it easier for customers to identify products that match their needs and also suggesting the best product based on the reviews [28]. It's possible to use a variety of recommendation systems for this goal. There are a number of drawbacks to these algorithms that include a lack of scalability and an inability to adapt to changing customer preferences [29]. A recommendation system based on customer behaviour and statistical analysis is developed in this research in order to address the issues raised above and to produce high realistic prediction results that can be used on an e-commerce site and improved in performance.

2. Literature Review

Issaoui et al. [1] proposed an E-commerce enterprise that can improve their marketing tactics by using recommendation techniques and product and service customization in order to better understand their customers' habits. If users are working with anonymized sessions that don't have any history of the user's activity, this gets even more challenging. The clickstreams of previous anonymous sessions are analyzed and clustered in this research to create a neural network prediction model. An anonymous online session and a few clicks on the model's interface are all it takes to get an accurate profile of a user. It can be utilized by the e-decision commerce's system to provide online suggestions and better tailor its offerings to the client's profile.

Lv et al. [4] proposed a model that considers people's attitudes, feelings, views, and feedback may all be gleaned via Twitter, which is one of the most popular social media platforms. Textual tweets can now be subjected to sentiment analysis in order to determine if they convey a good or negative message. This is a major improvement over the low classification performance of older techniques, such as Convolution Neural Networks and Bidirectional Long Short Term Memory (Bi-LSTM). The convolutional and maximum pooling layers of CNN can efficiently extract high-level local information, but they are unable to learn sequences of correlations. For deep learning, however, Bi-LSTM makes use of two LSTM orientations to enhance the contexts accessible, but it is unable to automatically extract features simultaneously. There is no way to get the best classification result while using only one CNN or one Bi-LSTM. This paper proposes a CNN and Bi-LSTM models integration framework. Tweets are transformed into numerical values by the implementation of the ConvBiLSTM word embedding model, and the CNN layer gets feature encoding as input to build lower dimension features, which the Bi-LSTM model uses to produce classification results.

Mu et al. [6] proposed an e-commerce supply chain that includes a manufacturer, a third-party solutions and services, and an e-commerce firm is examined in this article. The availability of a safety traceability system, the amount of freshness, the unit online sale value, and the unpredictable factor all affect the demand for fresh product on the market. Under various supply chain decision circumstances, the author built the game models. In order to better coordinate the supply chain, two types of contracts are proposed, namely, a unilateral cost-sharing contract and a consolidated rebate and income contract. Researchers investigate the effects of shifting consumer preferences in the market on supply chain decisions, supply chain earnings, and contract policy implementation. Numerical examples are used to illustrate the theoretical results and derivations. This research not only adds to the existing body of knowledge, but it also offers assistance for those involved in the local produce e-commerce supply chain function of production, operation, and sales.

Xu et al. [7] proposed a model forecasting whether customers would return for a purchase in the future, given that 98% of consumers do not purchase on their first visit. For example, providing coupons to consumers who are most likely to convert is an effective way of addressing this issue when strategizing about retargeting. Here, the author focused on two issues: market forecasting and consumer predictability. An important analytics measure for the retargeting process is determining the product's conversion rate and customer behavior modelling, which are the first steps in market forecast. Yeo et al. [8] proposed a joint modelling of both customer and product-level conversion trends depending on the well-studied purchasing decision process. The service provider can monitor customer-specific behavior after retargeting advertisements in order to anticipate if this specific client fits the economic model pass or fail. Using a market model for the former, and a new customer-specific forecast based on adaptive ad behavior attributes for the latter, the author make the predictions.

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Extensive experiments are conducted on the generated dataset built from a set of real-world site logs and remarketing campaign records.

Numerous research projects have been conducted on product recommendation. It has been used in a range of applications that focus on user-to-user and item to item interactions. Collaborative filtering (CF) can be used to offer suggestions for movies, articles, and even purchases. As CF approaches have some drawbacks, web mining strategies have been studied by Shang et al. [10]. It is the process of applying data mining tools to identify patterns in massive amounts of web data. Associative rules and page clusters are two further methods for seeing patterns in large amounts of data. Based on web usage and purchase decisions data, a system was developed to recommend products by Sun et al. [12]. The author was motivated by what customers wanted, and that's why the author developed these procedures. To assist with this, they compiled a list of the top N products recommended by diverse consumers over a given time period. In order to see if their proposed recommendation system worked, the online shopping mall ran a number of tests. Findings from the tests show that recommending products and services to customers at the right level is important.

Product suggestions were made using analysis methods and group production methodologies designed by Kwak et al. [13]. Relative weights of the frequency or monetary (RFM) variables were calculated using an analytic hierarchy technique. They employed clustering methods based on the weighted RFM value to construct a cluster of clients. A product recommendation was made for each consumer group using association rule mining. More dedicated customers are more likely to recommend products, whereas those less devoted are less likely to benefit from doing so. According to Domingo et al. [14], a system for offering customers with personalized product recommendations might be developed. The consumer's purchase habits were tracked using mining techniques in the recommender systems. The clock streams of customers were utilized to automatically acquire information about their product preferences and their associations with other products. A customer preference-based algorithm was utilized to determine the overall rating for each individual product. A system is used to compile a list of recommended products for each customer. In the experiment, they were able to show that their method not only saved customers time but also supplied them with accurate recommendations.

3. Proposed Method

Recommended systems serve clients by presenting a likely range of options from which they can select the best one. Customers may make more educated selections about which things to purchase by comparing costs, features, delivery schedules, and other factors of new and similar products. Recommender algorithms have been applied into e-commerce and other enterprises, such as online social and movie/music rendering sites. There is a lot of money to be made by these companies, as well as lessening the burden on consumers by allowing them to search and sort through an enormous amount of data. Shoppers can benefit from recommender systems, which learn how users use the system and recommend additional purchases based on what they have already purchased.

Features are extracted from the dataset using a feature extraction model. In the beginning, a Convolution Neural Network (CNN) model is used to extract as many features available from the dataset. More features necessitate the use of deeper and more complex convolution networks. To get the most information on a specific product, reviews about the products are considered and weight allocation is performed for better results. A CNN uses shared weights to extend spatially. Conventional neural networks, such as multilayer perceptrons [30], are used in CNNs. Input, convolution, activation, pooling, full connection, and output layers comprise the basic framework of a CNN. Because of their fault tolerance, parallelism, and self-learning capabilities, CNN-based recommender systems have an edge over more traditional methods. Complicated environmental data, hazy prior knowledge, and murky reasoning norms are no match for them. Because of this, the samples are allowed to have more flaws and distortions.

RNNs are nothing more than the combination of two separate recurrent neural networks (RNNs). Because of this design, the networks can access contains a series in both the past and the future at any one point in time. This strategy is different from unidirectional in that it preserves information from both the past and future at any given point in time, whereas unidirectional just preserves information from the present. The input of one LSTM layer model for product recommendation is provided to another layer for better processing and better product recommendations. The CNN based BiLSTM model in product recommendation is explained in the algorithm clearly. The BiLSTM model is shown in Figure 2.

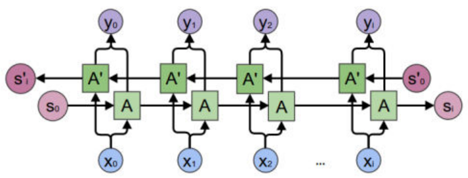

Fig 2: Bi-LSTM Model

One more LSTM layer is added to BiLSTM, which reverses the flow of information. To put it simply, the input sequence is regressed in the new LSTM layer. There are a number of techniques to merge the outputs from the two LSTM layers, such as averaging or concatenating them. The proposed Predictive Integrated Convolution Neural Network with Bi LSTM model is discussed in the algorithm.

Algorithm PICNN-BiLSTM

{

Input: Amazon Dataset {ADset}

Output: Product Recommendation Set

Step-1: Load the records from the dataset to analyze the user reviews of the fashion product considered for recommendation. The record loading and analysis is performed as

$$Recset\big(ASset(K)\big) = \sum_{p=1}^{M} getset(R) + getattribute(V(p)) + Th$$

Here R is the row in a dataset considered, V(p) is the value of a attribute in the dataset and Th is the threshold value considered for balancing the values in the dataset.

Step-2: The features are extracted from the dataset and the extracted features are used for training the model based on the correlation values. The highly correlated values are considered for the training of classifier for product recommendation. The feature extraction process is performed as

$$FVec(Recset(k)) = \sum_{p=1} \frac{ADset(p) + mean(ADset(p), ADset(p+1) + \lambda}{G}$$

Here λ is the similar product revies and feedbacks from users. G is the total records in the dataset.

Step-3: The correlation values of the extracted features are calculated and the highly correlated values are formed as a feature subset. The correlation calculation is performed as

$$Rcorr(FVec(k)) = \frac{\sum_{p \in ADset(M)} sim(Recset(p, p+1)) \times \lambda}{+\sum_{p \in ADset} |sim(p, p+1)|} + maxFVec(ADset(p), ADset(p+1)$$

Step-4: The BiLSTM model is initiated by setting the initial parameters and the initial variables are initialized and the hidden layer processing is triggered for the attribute processing and analyzing that provides training to the model. The BiLSTM based hidden layer attribute processing is performed as

$$i_t = sigmoid(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi})$$

$$f_t = sigmoid(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf})$$

$$g_t = tanh(W_{ig}x_t + b_{ig} + W_{hc}h_{t-1} + b_{hg})$$

$$o_t = sigmoid(W_{io}x_t + b_{i0} + W_{ho}h_{t-1} + b_{ho})$$

$$c_t = f_t * c_{t-1} + i_t * g_t$$

$$h_t = o_t * tanh(c_t)$$

$$p(R_{ij}|U_i, V_j, \sigma^2) = \prod (R_{ij}|U_i^T V_j, \sigma^2).$$

$$i'_t = sigmoid(W'_{ii}x'_t + b'_{ii} + W'_{hi}h'_{t-1} + b'_{hi})$$

$$f'_t = sigmoid(W'_{if}x'_t + b_{\prime if} + W'_{hf}h'_{t-1} + b'_{hf})$$

$$g'_t = tanh(W'_{ig}x_t + b'_{ig} + W'_{hc}h'_{t-1} + b'_{hg})$$

$$o'_t = sigmoid(W'_{io}x_t + b'_{i0} + W_{\prime ho}h'_{t-1} + b'_{ho})$$

$$c_{\prime t} = f'_t * c'_{t-1} + i'_t * g'_t$$

$$h'_t = o'_t * tanh(c'_t)$$

$$p'(R'_{ij}|U'_i, V'_j, \sigma^2) = \prod (R'_{ij}|U'^T_i V'_j, \sigma^2).$$

Here i is the input value activation vector, f is the forget gate activation vector, g is the input vector for activation, o is the output gate activation vector, c is the cell input activation vector, h is the hidden state vector.

$$Hlayer(i, o, g) = \sum_{p=1}^{M} Weight_{Recset(FVec(p))} + Feat\_Set(sim(Recset(i), Recset(i')) + \frac{(Rec(j, i)) + \sqrt{sizeof(ADset[M])^c}}{sizeof(ADset)}$$

Step-5: Using the reactions of other users, a technique called collaborative filtering might exclude items that a user would find interesting. The collaborative filtering model is applied on the feature set that is used for best product recommendation. The process is performed as

$$CF(ADset[M]) = \sum_{p=1}^{M} \frac{(Hlayer(Rec(h))) + min(Hlayer(Rec(h'))) + \sum_{p=1}^{M} max(Rcorr(o)}{sizeof(Cluster_{Set[M]})} + \sum_{p=1}^{M} max(Rcorr(o')$$

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Step-6: The product recommendation set is generated based on the features considered and with the collaborative filtering model. The prediction set helps the customers to find the best products. The process is performed as

$$PredSet[M] = \sum_{p=1}^{M} max(Weight_{Recset(FVec(p))}) + CF(sim(Hlayer(o), \left(Hlayer(o'''')\right) + h' - f') + \frac{(Recset(p, p+1)) + \sqrt{sizeof(ADset[M])^{Rcorr(p)}}}{sizeof(ADset)}$$

}

4. Results

Recommendation systems are in high demand due to the massive amounts of data generated by the ever-increasing use of the Internet and social networks. Here, we present a deep neural network-based recommender system that takes into account both user evaluations of movies as well as the visual characteristics of the film poster and trailer. RSLCNet, a hybrid movie recommendation system based on CNN and LSTM architectures, was created for this purpose. The LSTM network which receives user-rating sequences is used in the information retrieval engine of the proposed system to evaluate the dynamics of user interests. Based on the visual features in movie posters and trailers, as well as stars and directors, content-based filtering engines recommend related movies for users to watch.

The proposed Predictive Integrated Convolution Neural Network with Bi LSTM (PICNN-BiLSTM) Model is compared with the traditional CNN+LSTM Model and the results represent that the proposed model performance levels is high. To load data into a database or comparable application, records need to be accessed from a source dataset. The data loading accuracy levels from the considered data set of the proposed model is high. The Figure 3 represents the data loading accuracy levels of the proposed and existing models.

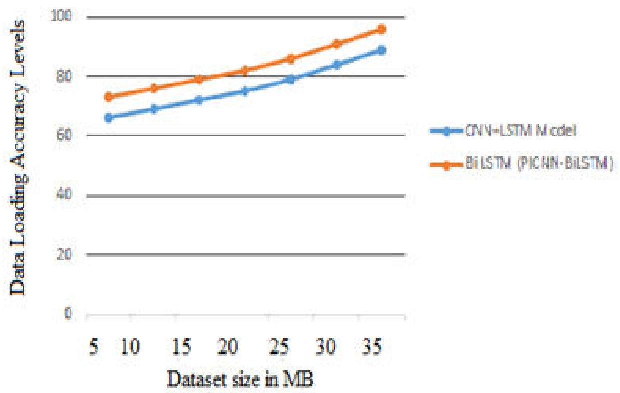

Fig 3: Data Loading Accuracy Levels

New characteristics can be extracted from existing ones in order to minimize the number of data points in a collection.

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Features can then summarize the majority of the information that was previously available in their original form. The features are used for training the model for better product recommendation. The feature extraction accuracy levels of the proposed and traditional models are shown in Figure 4.

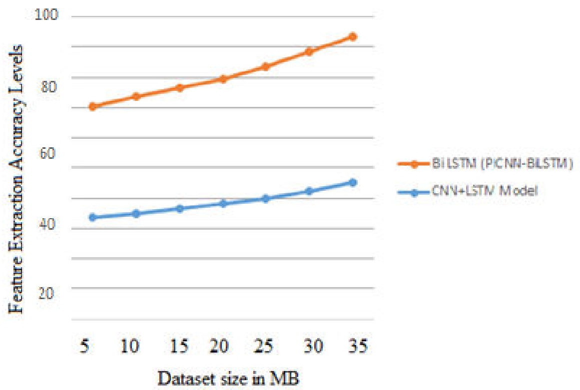

Fig 4: Feature Extraction Accuracy Levels

Feature extraction is a good technique to utilize when users want to reduce the amount of processing resources required without sacrificing any vital or relevant data. Extracting features from a dataset can help reduce the quantity of redundant data that is needed for product recommendation. The feature extraction time levels of the proposed and existing models are shown in Figure 5.

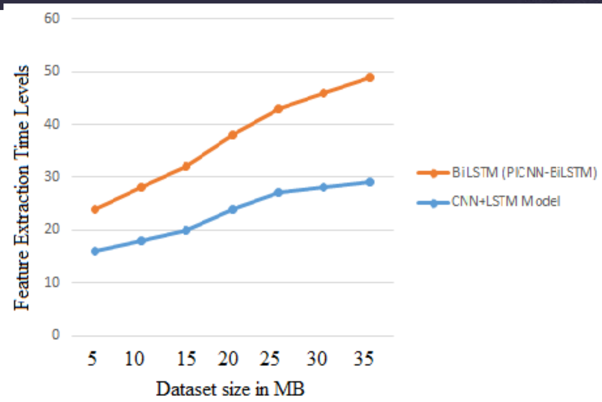

Fig 5: Feature Extraction Time Levels

When building a neural network, a hidden layer is a layer that takes inputs from another layer and then outputs data to another layer. One or more intermediary layers can be found between the input and output nodes. Because they are not visible from the system's inputs and outputs, the interior layers are frequently referred to as hidden layers. The hidden layer processing time levels of the proposed and traditional model is shown in Figure 6.

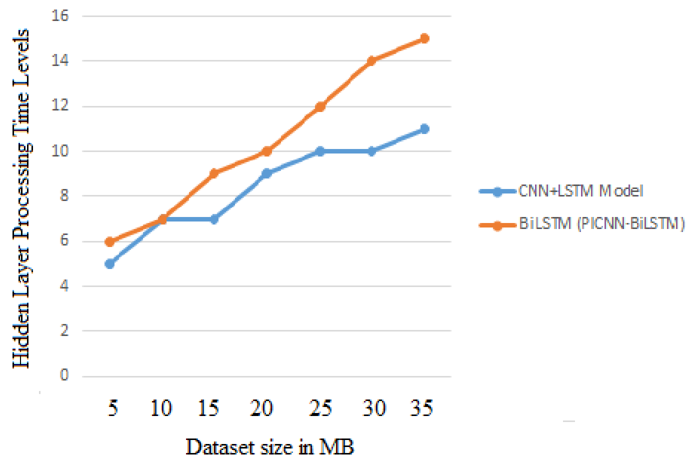

Fig 6: Hidden Layer Processing Time Levels

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Collaborative filtering model is a method for identifying products that a user might like based on the responses of other users who have similar interests. It does this by sifting through a huge group of people and selecting a smaller group of people who share the same interests as the user in question. Using this strategy in recommender systems to find correlations between user data and product offerings yield in better outcomes. The figure 7 represents the collaborative filtering model processing accuracy levels for product recommendations.

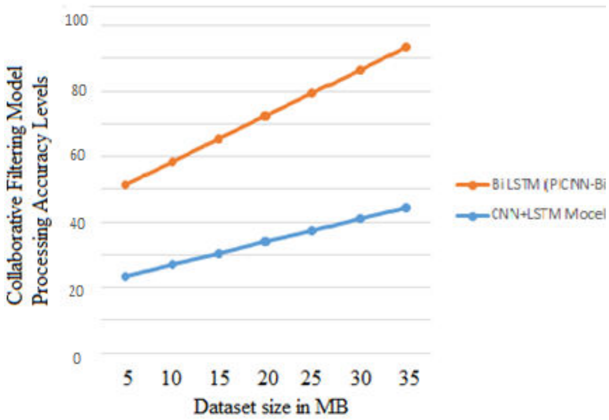

Fig 7: Collaborative Filtering Model Processing Accuracy Levels

A product is an object that the company believes its customers will be interested in and want to buy. In a physical business, skilled sales associates are usually the ones to provide advice. Customer qualities, browsing habits, and the current scenario all play a role in how product recommendations are generated in the context of an online store's customization strategy. This results in a more tailored shopping experience for the customer. The E-Commerce Product Recommendation Time Levels of the proposed and existing models are shown in Figure 8.

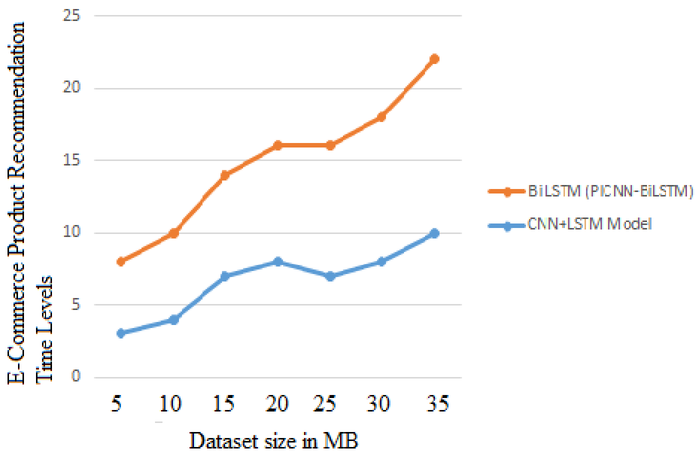

Fig 8: E-Commerce Product Recommendation Time Levels

A collection of algorithms is used by product suggestion engines to display users visitors relevant products. Using information such as geography, gender, and more precise information such as purchase intent, they are able to achieve this goal. Customer data will be analyzed by recommendation engines to determine what kinds of products and services are most appealing to individual customers and customer groups. They start serving contextually relevant promotions and product selections that appeal to particular

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customers and help increase sales. The Figure 9 represents that the proposed model accuracy levels in E-commerce product recommendation is high than the existing models.

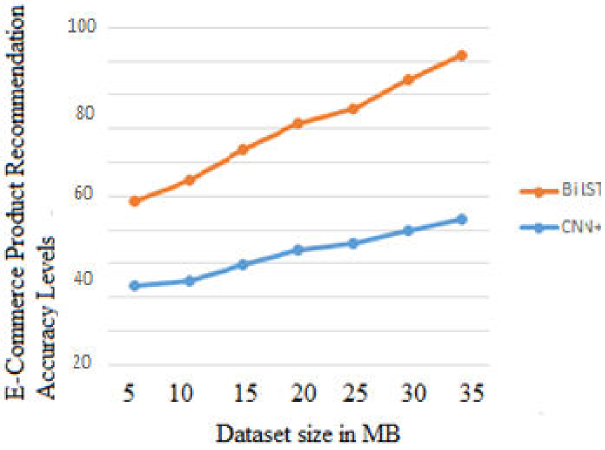

Fig 9: E-Commerce Product Recommendation Accuracy Levels

5. Conclusion

Predictive systems benefit consumers by recommending the most likely products through which they can choose. Comparing prices, features, delivery times, and other aspects of new and/or similar items enables customers to make informed decisions about which products to buy. Product recommendations can be made using a recommender engine. Different recommendation systems and evaluation approaches, as well as the system's challenges and problems are covered in this research. Building a recommendation engine based on Amazon's electronics data, as well as one that uses collaborative filtering, is also considered. Due to its vast range of applications in various fields, recommender systems have drawn a lot of interest and have been extensively explored in recent years. The use of deep neural networks in recommender systems is on the rise as a result of the study and use of deep learning methods. The success of contemporary recommender systems is largely dependent on their ability to interpret and apply the context of suggestion requests. On the other hand, when using deep learning algorithms to make recommendations, the significance of factors like the time and place of the advice is frequently overlooked. For text classification, a hybrid model using Bi-LSTM and CNN is proposed that is accurate for online product recommendation. The most correlated features are considered for training the model and the best product with better user feedbacks are considered for recommendation. The proposed model Future research could compare these findings with those of other techniques, such as weighted exponentially weighted averages and double simple exponential methods, as another possible direction of research to explore further.

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