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Optimizing Demand Forecast for E-commerce Sales Platforms Based on RNN-RBM Methodology

[1]Dr. Naveen Pol,
Associate Professor, ISBR Business School,
Bengaluru, India,
naveen.pol2007@gmail.com

[2]Dr. S. Arunarani,
Assistant Professor, Department of Computer Applications, FSH, SRM IST,
Chennai, India,
arunaprabhu07@gmail.com

[3]R. Thiru Murugan,
Associate Professor, Department of Business Administration, Kalasalingam Business School, Kalasalingam Academy of Research and Education,
Virudhunagar, India,
r.thirumurugan@klu.ac.in

[4]Dr. V. Divya,
Assistant Professor, Department of Information Technology, VELS Institute of Science, Technology and Advanced Studies (VISTAS),
Chennai, India,
divyavenkatraman1992@gmail.com

[5]Dr H Anwer Basha,
Associate professor, Department of Computer Science, Saveetha College of Liberal Arts and Sciences, Saveetha Institute of Medical and Technical Sciences
Chennai, India,
anwerbashah.sclas@saveetha.com

[6]Gagan Singh,
Assistant Professor, Department of BBA, Meerut Institute of Technology (MIT),
Meerut, India,
singh66gagan@gmail.com

Abstract **–Due to technical advancements in this digital era, particularly in the e-commerce sector, the corporate paradigm has changed substantially. A common platform for advertising products is online marketplaces, sometimes known as e-commerce platforms. Businesses in the increasingly competitive e-commerce space require a strong marketing plan to boost sales conversion and differentiate between the competitions. Selected features, preprocessing, and training of models all depend on correct sequencing. The proposed approach utilized the SG smoothing filter during the preprocessing phase. Principal component analysis (PCA) is a statistical method that can be employed in feature selection to decrease the dimensionality of a dataset that contains numerous associated variables. Precise control over the qualities is necessary for RNN-RBM training. This approach appears to be far more cutting-edge than the current RBM and RNN algorithms. A significant improvement in accuracy was noted in the results, which reached 96.33%.**

Keywords— Sales Conversion, Principal component analysis (PCA), Recurrent Neural Network (RNN).

I. INTRODUCTION

Tracking and communicating facts about consumers' purchases is now considerably easier than it was in the past, thanks to the proliferation of e-commerce platforms and IT. There has been tremendous growth in platforms' capacities to monitor and share real-time sales data with users. Items' intrinsic quality (such as their durability, beauty, and ease of use) and items' relative quantity of sales volumes are two factors that contribute to how buyers assess the overall quality of e-commerce platforms. Most individuals who shop online look for products that have a lot of positive reviews since those reviews highlight the product's best features. What consumers buy is heavily influenced by sales numbers. Based on data acquired from a website that analyses vendors' sales for wedding services, merchants with a history of greater sales likely to attract more clicks. There is a twenty percent spike in demand for the five most popular dishes in the catering industry once sales data for those dishes is available. Given that sales data has the potential to enhance product quality in general, it is beneficial to investigate how sales data influences consumer purchasing patterns and business profitability. China already has the largest population of internet users worldwide, and the country's online commerce market is booming. B2C e-commerce describes the great bulk of these kinds of online deals. Suppliers sell items and provide services directly to consumers in this model. Online marketplaces are the most common means of direct sales to customers. In recent years, a growing number of suppliers have started to prioritize business-to-consumer (B2C) strategies. Electronic commerce has had an effect on a growing number of Indian industries. Buyers and sellers can sign up for this platform to do business online. The e-commerce business is seeing rapid growth due to a number of factors, including an increase in disposable income among the middle class, better user experience, and the widespread usage of mobile devices. The e-commerce sector in India has exploded in recent years. This is due to many factors, such as increasing disposable income, the growth of cities outside of major cities, increased investment in logistics and warehouses, people's busy schedules that don't allow them to go to physical stores, the wide variety of products available online, and the proliferation of product categories on e-commerce platforms. A new model of global e-commerce has been all the rage recently, and it's centered on drugs. Extremely high requirements for product safety are required in the pharmaceutical industry due to the particular nature of the products. More risks and unknowns will befall consumers in the realm of pharmaceutical use and international trade. Clients will look for ways to mitigate these risks and uncertainties by making advantage of the wealth of information accessible online. A lot of people say that reading reviews online helps them decide what to buy since the system get a better idea of the product's quality. It follows that online reviews will likely have a substantial impact on sales of both products and services. This has been demonstrated time and time again by existing studies on internet reviews. However, the focus of these investigations was on the initial assessments rather than the following ones. Extra reviews are a new kind of internet review that customers have learned to recognize as bolstering the credibility of reviews.

II. LITERATURE SURVEY

Being famous now costs a fraction of what it used to because of the meteoric rise of social media and live streaming. There are a lot of people interested in making stuff up on the internet. Few of these people will ever be able to establish a

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distinct social reputation just on the basis of their accomplishments. If someone becomes famous through the internet, the proposed approach say that the system are an internet celebrity [1]. Online retailers have long been aware of the power of celebrity endorsements to sway consumers to buy. Sales and trust in online retailers are both increased when famous people endorse products on social media and encourage their followers to do the same. Online personalities are increasingly serving as brand ambassadors, bridging the gap between brands and consumers. The system interact with customers on social media and other online communities by making informative and convincing content. [2]Online celebrities are valuable for a variety of reasons, one of which being the social link between the celebrities the system follow and their individual followers (especially "super fans") social relationships amongst fan communities[3]. Many companies are moving their emphasis to online sales because of the abundance of user-friendly, affordable, and highly configurable e-commerce platforms. [4] The growth of B2B and B2C platforms is crucial to the success of these platforms since it enables buyers to easily track sellers' performances and ratings and provide comments on what the system have bought. One may tell how successful a vendor is by looking at the quantity of reviews the method have, both good and bad, posted online [5]. A lot of vendors may have gone to extreme lengths to resolve this matter. In a break from the traditional review approach that depends on plain old text and score ratings provided by customers, some companies engage in what is known as "fake positive reviews". Customers are led astray, their understanding of the deal skewed, and the system end up making bad decisions as a result [6]. Negative feedback drives out positive feedback, and consumers' perception of the usefulness of online reviews plummeted. In the context of a Customers feel bewildered about who to put their trust in such a deception. [7] There would be zero sales if people didn't trust each other. An example of a dimension-reduction attack is the Three-Body Problem, a concept from science fiction wherein the original three-dimensional organisms are deprived of their ability to exist and endure because their three-dimensional space is reduced to two-dimensional space.[8] Establishing an effective online social network could be a solution for sellers that do not partake in manufacturing phony reviews. This would help alleviate buyers' skepticism of online reviews. One of the main causes of this issue is the anonymity that the internet provides. I can see why consumers might be hesitant to trust unidentified sellers or reviewers. Sales model selection is an area that academics have been focusing on more and more recently. Many works on the topic have weighed the benefits and drawbacks of agency and resale models for different actors in the supply chain in different contexts [9] primary elements influencing distribution channel selection Bibliography. [10] While analyzing how online shopping has changed the landscape for brick-and-mortar businesses, took into consideration discovered that the preference for resale or agency sales platforms is influenced by factors such as the impact of electronic channel sales on conventional channel demand,[11] the effects of brick-and-mortar demand spillover on the choice of platform sales model, and more. In a supply chain with a single online retailer and one supplier, [12] examined how suppliers' sales model selections were affected by their information sharing method. When production costs were low, suppliers would use agency or resale models. When production costs were high, resale was the only option. [13] examined the impact of market size and data-driven marketing on platform sales model choice, and the method found that when data-driven marketing grows more efficient, platforms are more inclined to use resale models. Some writers have thought about how market competitiveness affects sales model selection. The field of corporate social responsibility (CSR) research has recently grown popular. Businesses are expected to voluntarily assume specific ethical, legal, and financial responsibilities as part of their corporate social responsibility (CSR) efforts, which are outlined by [14]. This includes taking stakeholder interests into account alongside their own financial ones. Still, many prefer to shop online, even though the system may be unsure of the quality or value of the products the system select. The reason behind this is that consumer demands vary greatly. [15] Only with access to publicly available product details and reviews can consumers make a well-informed purchase decision. However, issues regarding product quality are still frequently voiced by customers. [16] In response, several well-known platform companies are establishing centers to assess product quality as part of their corporate social responsibility initiatives. [17] Doing so shows that companies value their clients, provides the greatest proof of product quality, and wins their trust. [18] The needs of buyers, meanwhile, are becoming more diverse. Amazon Web Services (AWS) and Alexa, its smart speaker, are two examples of how the company is working to better serve its customers. While eBay does offer business-to-business (B2B) transactions, its primary concentration is on consumer-facing marketplaces like C2C and B2C, while Covisint is a B2B platform for the automobile sector [19]. These online markets gave rise to these digital platforms. In addition to connecting buyers and sellers, these platforms facilitated the interchange of goods, services, information, and money by providing an institutional framework for market transactions [20]. Acceptance, governance, design, success, and economic impact are only a few of the many subjects covered in literature on electronic markets [21]. Research on performance has lately started to make use of a number of novel theoretical frameworks, including a strategic capacity approach. Many of the advantages that larger organizations have in the marketplace can be eaten away by smaller ones when it comes to possibilities to expand into new markets, enhance communications, and find suppliers through online marketplaces.

III. Proposed System

Choosing between the resale and agency modes of sales on e-commerce platforms can be a dilemma for a manufacturer with three channels direct sales, traditional retail, and e-commerce platforms. This essay investigates the topic in detail. Considerations such as market share, pricing competition, and commission rate are used to design two leader-follower models. Both conventional stores and online marketplaces follow one approach, while manufacturers take the lead in the other.

A. *Preprocessing:*

A popular filter for pretreating e-commerce sales platform is the SG smoothing filter. After applying this low-pass filter to the spectra, all high-frequency noise is eliminated while low-frequency signals are allowed to pass through. Also, SG filtering uses the weighted-average method for the moving window and relies on the local polynomial curve fitter to determine the best results. Although it is not a straightforward constant window, the weighting coefficient is obtained by fitting the least squares of a certain higher-order polynomial to a sliding window [22]. It boils down to gradually bringing the rebuilt curve closer to the original curve's upper envelope. Using the SG method with denoising based on smooth filtering could improve spectrum smoothness and reduce noise interference. One way to explain SG filtering is with the following statement:

$$R_k^* = \frac{\sum_{n=-h}^{h} T_n R_k}{I} \quad (1)$$

The filtered data is represented by R_k, the number of data points in the sliding window is $I(I = 2h + 1)$, the width of the window is $2h + 1$, and the rebuilt spectral data is R_k^*. T_n is the filtering coefficient. The practical implementation of SG filtering relies on two parameters: the filter window width and the order of the smooth fitting polynomial. A broader filter window generates a smoother spectrum, and this width can affect the smoothing outcomes. The fitting polynomial order also affects the filtering results. A higher rank is indicated by a better match. It used a 20-item filter window and a fitting polynomial of order 2 for this proposed.

B. Feature Extraction:

1) PCA:

One statistical method for dealing with datasets that have a lot of associated variables is principal component analysis (PCA). Using the concepts of variances and co-variances, it preserves the dataset's variety to the fullest extent possible. In order to make the dataset less complex, the proposed approach follow these steps. Data reduction to a more manageable span, also known as data normalization. Determining the relationships and connections between the attributes of a dataset by calculating the covariance matrix. In order from largest to smallest, the eigenvalues of the eigenvectors can be calculated using the covariance matrix. Locate the main part. When generating the first principal component, the most significant eigenvector the one with the highest eigenvalue is taken into account. Removing the main, less important components of the data reduces its dimensionality. Rearranging the initial data using the final principal components will decrease the dataset's size. One method for discovering relationships in a dataset is principal component analysis (PCA) [23]. Using a covariance matrix, one can see how highly connected the variables in the dataset are. Due to their bias and duplicated information, heavily dependent variables reduce the model's overall performance, therefore identifying them is vital. Covariance matrices are mathematically represented as $b \times$ b matrices, where b is the dimension of the dataset. Each row in the matrix represents a pair of variables and their covariance. The eigenvectors and eigenvalues, derived from the covariance matrix, are the mathematical structures utilized to determine the principal components of the dataset. A new set of variables, the principle components, is generated once the initial set of variables is obtained. The method of calculation ensures that the newly obtained variables are very significant and fully independent of each other. The primary components are now compact and contain much of the critical material that was scattered throughout the initial variables. Computing five main components is standard procedure when working with five-dimensional datasets. The first component should have the biggest quantity of information; the second should contain the maximum amount of information remaining after the first, and so on. Pair of algebraic formulation is produced by the calculation of eigenvectors and eigenvalues together. Every eigenvector has an associated eigenvalue. This computation requires a certain number of eigenvectors, which are determined by the data dimensions. A key assumption of eigenvectors is that the covariance matrix can identify the most variable data points. Principal component analysis makes use of eigenvectors, so a larger data variance yields more informative results. In this case, the eigenvalues are shorthand for the scalars of each eigenvector. The primary components of the dataset are computed using eigenvectors and eigenvalues respectively. The eigenvectors and eigenvalues have been calculated and arranged in decreasing order of importance, with the eigenvector with the highest significance acting as the initial main component. Simply deleting the main components of insignificant variables will reduce the data's dimensionality. Finally, a matrix known as the feature matrix is constructed during the principal component computation. For a complete picture of the data, this matrix incorporates all the most relevant factors. The last step in principal component analysis (PCA) is to rearrange the original data using the final principle components, which represent the most important and substantial information in the dataset. The transpose of the original dataset, multiplied by the transpose of the obtained feature vector, will produce principal components that will substitute the original data axis.

C. Model Training:

1) RNN-RBM:

Here is the RNN-RBM model that the proposed approach think would work. It contains every part of the structure of an RNN-RBM model. The model is made up of four sections. The proposed method begins with dense byte-level embedding, which converts each packet byte into a distributed vector. Next, the scattered vectors will be encoded and compressed by the multi-layered RBMs. Each packet has a fixed length feature vector that the RBM model uses since packet durations vary. Thirdly, an RNN model is applied to the micro-flow representation prior to constructing the entire flow. Lastly, it employs a Softmax classifier to detect the maliciousness of the traffic and identify the type of micro-flow.

a) Byte Representation:

Each packet uses a certain amount of bytes. The research suggests that CNN models can detect fraudulent traffic if the system treat bytes as picture pixels and packets like data. Despite the formal similarities to language, it would be incorrect to treat network data as though it were pixels and bytes. In the realm of NLP, word embedding is currently trending. Mapping bytes into a high-dimensional vector is a similar idea used for online data processing; it's called byte embedding or byte representation. In this system, the proposed approach employ distributed embedding to stand in for bytes. The representation of the bytes that comprise the network packets is $\{p_1, p_2, \dots, p_i\}$ When i is the number of bytes in the packet. A k-dimensional byte-embedding vector, used as an input to an embedding function, assigns a unique value between zero and one to each byte. Here is the mapping packet as it is presented in the contract:

$$q_{packet} = \{d_{emb}(p_1), d_{emb}(p_2), \dots, d_{emb}(p_i)\} \quad (2)$$

in which the following RBM model takes as input the vector of packets that have been joined by byte vectors, denoted as q_{packet}.

b) Packet Representation:

A small number of recent researches have achieved state-of-the-art performance in several detection tasks by modeling packets using RBMs. It also uses an RBM model to create packet representations in this system. Packet vectors were created in the prior part by use of distributed embedding. Since each vector contains a unique amount of bytes, its lengths are also distinct. The RBM model is limited to taking in vectors of specified length for the processing that follows. Therefore, then trim the longer packet and pad the shorter one with zeroes to reconstruct the ones with a set length. There will be a discussion of the reconstruction's effects.

The RBM model is a two-layer energy model that uses both exposed and concealed neuron units. It is to minimize the K-L distance, which is the distance between the visible and concealed layers. The visible layer receives its inputs from the outputs of a sliding window. Some possible RBM models using NV visible units and NH hidden units are as follows:

$$b(q) = \frac{1}{W}\sum_{m} b(q,m) = \frac{1}{W}\sum_{m} e^{-C(q,m)} \qquad (3)$$

$$b(m) = \frac{1}{W}\sum_{q} v\,(q,m) = \frac{1}{W} e^{-C(q,m)} \qquad (4)$$

where the energy function is denoted by $Z = \sum_{q,m} e^{-C(q,m)}$ *and* $C(q,m)$. This is the energy function:

$$C(q,m) = -\sum_{n=1}^{I_m}\sum_{k=1}^{I_Q} z_{nk} m_n q_k - \sum_{k=1}^{I_Q} p_k q_k - \sum_{n=1}^{I_M} e_n m_n \qquad (5)$$

where the hidden layer's units are represented by p_k and the visible layer's units by q_k, and the weight associated with the link between the two layers is z_{nk}, which is also a real-valued parameter. The RBM paradigm uses a packet vector in the visible layer, whereas the hidden layer generates the packet representation. The RBM model is trained using a CD-k technique in an unsupervised manner. In the RNN model that follows, each packet's vector is copied into a new set of vectors denoted as $q_{packet,t}$,it represents the packet's position in the micro-flow.

c) Micro-flow Representation:

Since the micro-flow is best understood as a time-series of packets, the RNN model is employed after the RBM model outputs have been obtained. In theory, recurrent neural networks (RNNs) can map all inputs to all outputs, in contrast to multilayer perception (MLP) and other traditional neural networks, which may only map one way from inputs to outputs [24]. Let will go over recurrent neural networks in this article. One popular recurrent connection in RNN models is three layers, which is similar to a traditional neural network. Nonetheless, the inputs' histories are preserved by the concealed layers. Consequently, the RNN model necessitates a sequential arrangement of inputs. The outputs of the RBM were previously described as a set of vectors denoted by the symbols $q_{RBM,c}$. Consider this RNN model: inputs are I_N units, hidden layers are I_M units, and outputs are I_X units.

$$x_{rnn}^{c} = \sum_{m=1}^{I_m} z_{mx} x_m^c + p_m \qquad (6)$$

where x_m^c are the hidden layer's outputs in step t, $z_{mx}$is the weight from the hidden layer to the output layer p_m, and m_1 and 1 are the hidden layer's bias parameters. A hidden unit's output looks like this:

$$x_m^c = \delta(v_m^c), v_m^c = \sum_{n=1}^{I_N}\left(z_{nm} q_{RBM,c} + p_n\right) + \sum_{m'}^{I_M}\left(z_{m'm} x_m^{c-1} + p'_m\right) \qquad (7)$$

$z_{nm}$is the real-valued weight between the hidden layer and the input layer, and $z_{m'm}$ is the neural activation function $\delta(.)$ G is the weight in real values between the hidden and recurrent layers, and $p_n$and p'_m are the input and recurrent layers' bias parameters, respectively.

IV. Result and Discussion

At the same time that e-commerce platforms' sales scales are skyrocketing, consumer evaluation data on commodities is also expanding at an exponential rate. Improving the development of e-commerce platforms necessitates prompt consideration of the matter of how to derive valuable insights from massive volumes of consumer evaluation data utilizing big data visualization and analysis technologies. The data utilized for online store reviews, on the other hand, is typically traditional big data i.e., unstructured and growing at a rapid pace.

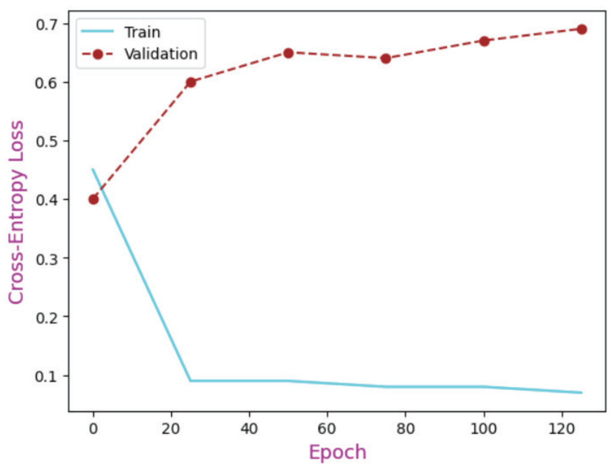

Fig. 1. Cross-Entropy Loss vs Epochs RNN-RBM Training and Validation Graph

A dropout layer with a dropout value of 0.1 was included in an effort to make the network more generalizable. Last but not least, the model's final layer was configured as a dropout layer using sigmoid activation clause.

Figure 2 displays the training graph of RNN-RBM vs epoch for accuracy. A novel approach to enhancing the accuracy of the sentiment analysis was part of the experiment. Another RNN-RBM model was built; this time, a pre-trained will be used for training.

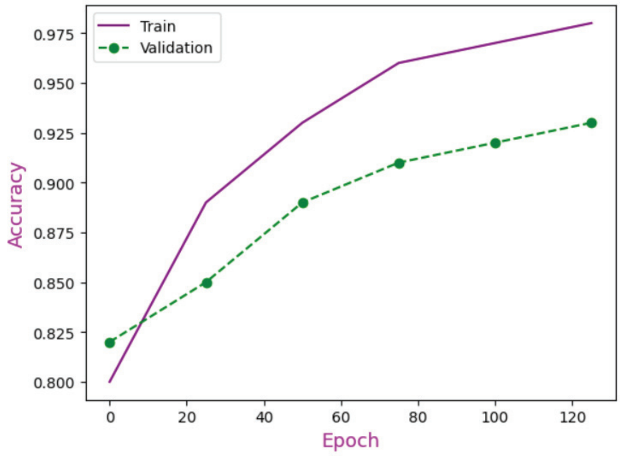

Fig. 2. Training and Validation Accuracy of the Model

TABLE I. PERFORMANCE RESULT (%)

Models	ACCURACY	F1	PRESICION	AUC
RNN	0.8964	0.8738	0.8800	0.9024
RBM	0.9215	0.9080	0.9136	0.9526
RNN-RBM	0.9633	0.9432	0.9579	0.9741

Table 1 shows the average performance of three models the best of which is the RNN-RBM model trained for features per class for each e-commerce sales platform.

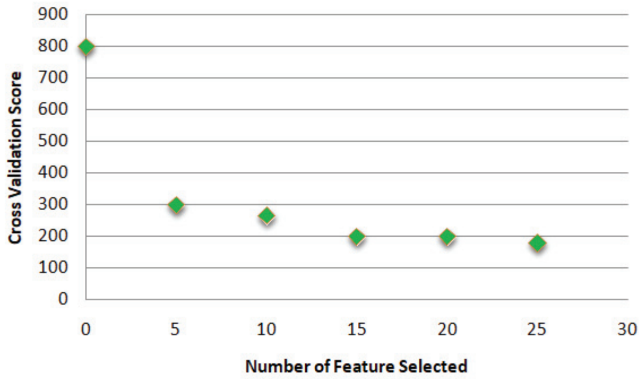

Fig. 3. RNN-RBM Method Feature Selection Curve

The traits of online sales dictate which criteria are most important for sales forecast. The main characteristics are 35. To determine how much of an effect the features have on sales, the RNN-RBM approach is employed. Figure 3 shows the outcome of RNN-RBM.

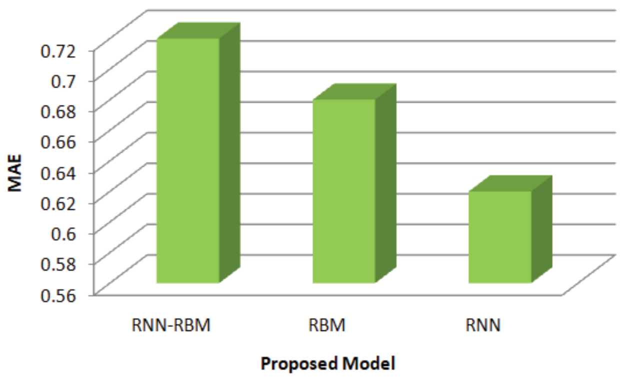

Fig. 4. Recommendation Algorithms and Data Sparsity

Figure 4 shows the results of the experiment. The suggestion quality stays the same as sparsity diminishes, as shown in Figure 4. A sparsity of 0.72 yields the best suggestion quality in this experiment. A sparsity level of 0.72 was employed for the datasets in the following experiment.

V. CONCLUSION:

Looking at the e-commerce platform's CSR initiatives from the perspective of agency sales, wholesale sales, and hybrid sales modes, this article delves into the topic. This presupposes that the manufacturer controls both the brick-and-mortar storefront and the online marketplace. With the e-commerce platform as the main actor and considering variables such as the potential market size of the platform, the sensitivity of consumers to the level of CSR input, and the CSR input cost coefficient, the proposed approach constructed a Stackelberg game model under the agency sales, wholesale sales, and hybrid sales modes. The SG smoothing filter was employed throughout the preprocessing step. In feature selection, principal component analysis (PCA) is a statistical tool for reducing the dimensionality of a dataset with many related variables. It used RNN-RBM to train the proposed model. The suggested method outperforms the RBM and RNN models in terms of average accuracy, coming in at 96.33%.

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