Received: June 16, 2023. Revised: August 30, 2023.


*International Journal of*
Intelligent Engineering & Systems

http://www.inass.org/

# An E-Commerce Based Personalized Health Product Recommendation System Using CNN-Bi-LSTM Model

**B Ramakantha Reddy[1] R. Lokesh Kumar[1]***

[1]*School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, Tamilnadu, India*
* Corresponding author's Email: lokeshkumar.r@vit.ac.in

**Abstract:** With the increasing complexity of contemporary E-commerce recommender systems, personalized health product recommendations have become a challenging task. Existing methods predominantly rely on latent natural language features extracted from product descriptions, lacking transparency and user engagement. While recent item-representation-learning algorithms integrate pre-defined attribute data, they still struggle to provide accurate recommendations and detailed explanations due to sporadic relationships between stated qualities and the recommendation process. To address these challenges, we propose an E-commerce based personalized health product recommendation system using a CNN-Bi-LSTM model. Our system leverages pre-trained CNN-based transfer learning models, such as AlexNet, Google Net, and ResNet-50, for predicting health products, while the Bi-LSTM acts as a numerical function to provide ratings. The CNN-Bi-LSTM recommendation system utilizes attribute-specific representation extraction methods, resulting in a more robust compatibility model and improved recommendation effectiveness for health products. The proposed approach is evaluated on two datasets: The health-product dataset and the Flipkart health product dataset. The health-product dataset comprises 20,726 products, including health supplements (14,871 items) and fitness-related products (13,663 items) recommended by experts. The Flipkart health product dataset contains 21,889 healthcare products with essential information like name, price, MRP, discount, and ratings. Comparative analysis against existing methods, such as W-RNN and Improved SVM, demonstrates the superiority of our CNN-Bi-LSTM model. The evaluation metrics, including accuracy (95.52%), recall (88.31%), and user coverage (89.51%), highlight the effectiveness of our recommendation system in providing more accurate and relevant personalized health product recommendations. For the aforementioned dataset, the AUC and hit rate of the proposed method are contrasted with those of existing methods. The findings were gathered to demonstrate that the suggested approach performs better when compared to the current recommendation systems.

**Keywords:** CNN-Bi-LSTM, Healthcare product recommendation system, E-commerce, AlexNet, GoogleNet, ResNet-50.

## 1. Introduction

Due to the exponential growth of online platforms, notably social media and E-commerce, consumers need smart ways to manage information overload [1]. Online retailers propose products based on past purchases and product attributes [2]. E-commerce recommends things that may interest clients, while internet advertising recommends information that matches their tastes [3]. A health product recommender system gives patients or health professionals individualized health product or service recommendations. Patient data, medical history, and other information are used to create suggestions [4].

Personalized health product recommendations can enhance patient outcomes. Based on a patient's medical history and symptoms, the system may prescribe prescriptions, equipment, or services. This may improve treatment and lower healthcare expenses [5].

Health product recommender systems can use content-based filtering, collaborative filtering, or hybrid methods. Collaborative filtering recommends products based on related people's tastes and actions, unlike content-based filtering. Hybrid methods yield more accurate and diverse recommendations. Knowledge, decision, and virtual recommendation systems have been developed for health product issues [6]. E-commerce systems rely on the recommendation system to boost sales and satisfy customers [7]. Based on user desire, satisfiability, rating, merits, and brand, the health product recommendation system makes effective recommendations [8, 9]. This may yield recommendations that hold many users' interest in the short term, but it will also continually suggesting the same things [10]. CNN selects products based on similarity in the recommendation system. CNN generates features from qualities and combines them with others to predict product recommendations [11, 12]. Filtering-based CNN can pre-train CNN features based on user preferences using the recommendation profile [13, 14]. Health product recommender systems can use RNN, LSTM, and transfer learning models. These models use temporal and non-temporal patient data to make more precise and individualized suggestions. Managing missing data and guaranteeing fairness and openness in health product recommender systems are still research gaps and concerns.

This research uses pre-trained CNN-based transfer learning models and bi-long short-term memory (Bi-LSTM) to recommend health goods based on 1–5 ratings.

The paper's main contributions:

- An e-commerce recommendation system improves customer experience when shopping online.
- To create an efficient recommendation system, three CNN architectures—Alex-Net, Google-Net, and Res-Net-50—are investigated.

To list recommendations in descending order from 5 to 1 so customers can choose the highest-rated health product. Section.2 covers similar works in the paper's rest. The proposal discusses it in section 3. Section 4 presents findings and empirical analysis. Section 5 is the paper's conclusion.

## 2. Related works

Recommender systems depend on patients and products. Inferring patient preferences from data is vital. A utility matrix shows each patient-item pair's preference for that item. Therefore, recommender systems are item-based or patient-based. Customers rate products using a recommendation engine [15]. A patient-based recommender engine can offer the item to the patient based on their similarity, even if they haven't rated it. An item-based recommender system predicts patients using item similarity. Prediction begins using recommender system data [16].

(1) Information collection: The patient's features, behaviors, and resources are used to develop a patient profile during this phase. A recommender engine needs a precise patient profile. Hybrid, implicit, and explicit feedback form the basis of a recommender system. Explicit feedback asks clients about their product interests, while implicit feedback observes customer behavior.

(2) Learning phase: Feedback from the first phase is employed. After a learning algorithm analyzes feedback, patient attributes are output [17].

(3) Prediction/Recommender phase: Patients choose their favorite products. The system can forecast using the model, memory-based knowledge, or patient behavior by analyzing input from the information collecting phase.

Recommender systems have grown in healthcare. An organization or person with internet connection can save and retrieve health information online. Patients have more internet health resources. Recommender systems improve information accuracy. Personalized context-based health information lets patients control their health data.

The Collaborative assessment and recommendation engine (CARE) [18] uses CF techniques to predict patient disease. It compares the patient's medical history to similar cases. It detects comparable users and diseases using vector similarity and inverse frequency methods. A temporal factor improves the prediction and distinguishes between a chronic sickness and an isolated incidence. Computer science has been utilized to calculate health recommendations. A review [19] found two HRS techniques. Information retrieval (IR) generates suggestions based on the user's informative interests. Internet marketing and advertising also uses the recommendation algorithm (RA) strategy. This yields preferences-matching outcomes, unlike the IR technique.

Knowledge-based strategies are better for e-learning than collaborative filtering and content-based methods. If two students have similar ratings but different qualities, they need different suggestions [20]. E-learning learners vary in prior knowledge, learning history, and skill level. The knowledge-based method uses ontologies to customize user profiles, unlike collaborative filtering and content-based RAs that merely offer products based on ratings. Combining learner-specific domain knowledge with instructional materials enhances recommendation quality and reduces cold-start and rating sparsity problems.

In the article personalised diet management system based on recurrent neural networks for chronic diseases [21], RNNs predict a user's daily energy expenditure and advise meal plans based on their dietary choices and medical conditions. Personalised exercise recommendation system based on recurrent neural networks for health management [22] uses RNNs to predict a user's exercise patterns and recommend personalised exercise plans based on fitness level and health goals.

Research works a recurrent neural network for individualized health monitoring and recommendation [23] uses RNNs to forecast a user's health status and offer individualized health interventions based on their medical history. Research work a recurrent neural network approach for personalized sleep quality recommendation [24] uses RNNs to predict a user's sleep quality and prescribe personalized sleep therapies based on sleep data and lifestyle parameters. Research work personalized health product recommendation system utilizing recurrent neural networks [25] predicts a user's health state and recommends personalized health goods based on health data and preferences.

A CNN-LSTM-based hybrid deep learning model for predicting and suggesting health items for health-related issues [26] reduced admission rates. EHR clinical and demographic data projected probability. The model's AUC was 0.78 on real-world EHRs. A CNN-LSTM-based personalized recommendation system for chronic disease management was proposed in [27]. Patient recommendations were based on EHR physiological, behavioral, and demographic data. The proposed system had 0.88 precision and 0.80 recall on a real-world EHR dataset. A CNN-LSTM-based recommendation system for individualized mental health interventions was suggested in [28]. The system tailored mental health interventions using social media text and wearable physiological data. A real-world mental health dataset yielded 0.72 accuracy for the suggested approach.

A Bi-LSTM-based strategy for drug recommendation using EHRs was proposed in [29]. Patients received tailored medicine recommendations using EHR temporal and semantic information. The proposed method had an F1-score of 0.80 and accuracy of 0.86 on a real-world EHR dataset. Bi-LSTM-based deep learning model for predicting and suggesting health goods to reduce admission rate [30] was proposed. EHR clinical and demographic data predicted probability. A real-world EHR dataset had an AUC of 0.79 for the suggested model. Research works [31] developed a hybrid strategy for personalized health recommendation utilizing Bi-LSTM and collaborative filtering. Users received individualized health advice using temporal and user-item interaction aspects. On a real-world health record dataset, the proposed method had 0.64 precision and 0.50 recall. a Bi-LSTM-based personalized recommendation system for medical insurance products [32]. Users received individualized insurance product suggestions based on demographic, behavioral, and social network data. A real-world dataset of medical insurance records yielded 0.87 accuracy and 0.82 F1-score for the suggested approach.

The above research shows deep learning-based health product recommendation systems work. These methods can use temporal, non-temporal, and semantic characteristics from EHRs, social media, and wearables to provide individualized chronic illness management and mental health interventions. However, more research is needed to assess the interpretability, scalability, ability to handle missing and noisy data, and generalizability of these approaches across health settings and populations.

Recurrent neural network and expression distribution approach were used to improve E-commerce recommendation [5]. Recurrent neural networks were improvised and their hidden layers transferred data. The E-commerce recommendation system can quickly extract information and predict accurately. The E-commerce recommendation system also worked with real-time data. The recommended data was aberrant, uncontrollable, and noisy. In machine learning-based E-commerce image recommendation research [33]. Singular value decomposition (SVD) was used to perform principal component analysis (PCA) on the collected data. K-means++ was used to find clusters for comparable objects. The method provided similar photos in E-commerce platforms faster and helped users choose products. Suggestions collapsed when the input image structure changed.

Deep learning-based recommendation systems, while promising, are not without their limitations. One major concern is the interpretability of these models, as their complex architectures and numerous parameters make it challenging to understand the reasons behind specific recommendations. Additionally, deep learning models often require a substantial amount of data to perform well, which can lead to data sparsity and cold-start problems, especially for new or less active users. Scalability can also be an issue, as training and inference times may increase significantly with large datasets and user bases. Moreover, deep learning models can be

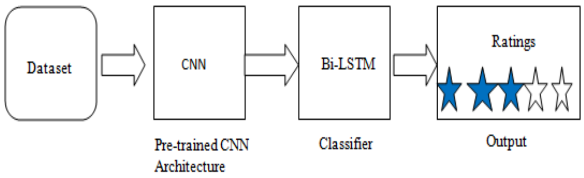


Figure. 1 The proposed health product recommendation system

sensitive to noisy or anomalous data, affecting the quality of recommendations. Lastly, privacy and security concerns arise when dealing with sensitive healthcare data, requiring careful consideration of data protection measures. While the research works presented in section 2 demonstrate the efficacy of deep learning-based approaches for health product recommendation, addressing these potential limitations remains a critical area of future research.

To address these limitations, future research should focus on developing more interpretable deep learning models, incorporating techniques for handling data sparsity and cold-start problems, and considering privacy-preserving approaches while leveraging healthcare-related data. Additionally, conducting more extensive evaluations on diverse datasets with real-world scenarios will provide a better understanding of the strengths and weaknesses of deep learning-based health product recommendation systems.

## 3. Personalized health product recommendation system using CNN-Bi-LSTM

This study considered various architectures of CNN to solve the multi-objective problems using the Bi-LSTM classifier. The proposed pre-trained CNN models with Bi-LSTM architecture can predict the scenarios of the future. The Bi-LSTM is developed based on the analysis of time series data and they can be trained in different sections. The performance of the CNN-Bi-LSTM architecture is similar to feed-forward neural networks that are well-suited for the training process. The process involved in the recommendation system using CNN-Bi-LSTM is represented in Fig. 1.

### 3.1 Dataset

This paper is employed using two datasets as Health-product dataset and the Flipkart product dataset which provides information regarding health products and their associated information.

**Health-product dataset:** This dataset contains product reviews and ratings from Amazon for various health-related products, such as supplements, medical devices, and fitness equipment. This dataset consists of 20,726 products which include 14,871 products of medical device items related to health supplements and 13,663 items related to fitness that are originated by experts.

**Flipkart health product dataset**: The dataset has 21,889 healthcare product information such as name, price, MRP, discount, and also ratings which helps to categorize the most demanded products [32].

The pseudo code for personalized health product recommendation system is given in following algorithm.

Algorithm1: CNN-Bi-LSTM algorithm for product recommendation system

**Input: E-commerce benchmark dataset**
**Output: Specific recommendations**
**Step1:** load the data along with product reviews, features, ratings
**Step 2:** perform data- preprocessing using K means. Smote(Dataset)
**Step 3:** initialize transfer learning models **AlexNet, GoogleNet, and ResNet-50** with parameters and perform model training
**Step 4:** after the training, the pre-trained CNN model outputs a feature vectors vectors $F_{t_i} \in R^{D\times7\times7}$ and $F_{b_j} \in R^{D\times7\times7}$ with a feature map of size 7x7. Where $F_{t_i}$ and $F_{b_j}$ are the feature vectors.
**Step 5:** As the health products exhibits different distribution features, the model will consider different qualities by creating second level of items classification using log based cross-entropy. The pre-trained CNN models and feature vectors are trained to extract atomic attributes for item along with its category as

$$\hat{y}\ item = softmax\left(W^{cat}V_{item}^{gl} + b^{cat}\right),$$
$$L_{category} = \sum_{item \in T\ \cup B} y_{item} \log(\hat{y}\ item)$$

**Step 6:** after extracting features using pre-trained CNN models, a BI-LSTM model is trained prediction on product recommendation.
**Step 7:** The model will built an **Attribute model for product pair ($t_i$ and $b_j$).**

$$M_{ij}^{compat} = (A_{t_i} W^{c_i c_j})W^{compat}(A_{b_j} W^{c_i c_j}) \in R^{K\times K}$$
$$M_{ij}^{affinity} = v_{t_i}^{attn} \otimes v_{b_j}^{attn} \in R^{K\times K}$$

Received: June 16, 2023. Revised: August 30, 2023. 

$$M_{ij}^{weighted\ compatibility} = M_{ij}^{affinity} \odot M_{ij}^{compat} \in R^{K\times K}$$

$$\hat{y}_{ij}^{compat} = \sum_{K=1}^{K}\sum_{K'=1}^{K} m_{kk'} \in M_{ij}^{weighted\ compatibility}$$

**Step 8:** For each product pair, a rank is assigned using a ranking loss function

$$L_{rl} = -\sum_{(i,j,j')\in D} \ln\left(\sigma\left(\hat{y}_{ij}^{compat} - \hat{y}_{ij'}^{compat}\right)\right)$$

**Step 9:** Based on the raking, the model will generate Top N recommendation using attribute specific recommendation

### 3.2 CNN-Bi-LSTM architecture

CNN solves processing issues in object recognition tasks. To anticipate the best product based on the user's previous purchase, three CNN architectures—AlexNet, GoogleNet, and ResNet-50—are evaluated. The Bi-LSTM helps rate products numerically. Bidirectional LSTMs, also known as Bi-LSTMs, are sequence processing models with two LSTMs that receive input forward and backward. Bi-LSTMs give the network access to more data, improving algorithm context. Bi-LSTM can use information from both sides. The convolutional layer stores product information and projects the CNN. This work uses CNN and Bi-LSTM to create a powerful recommendation system. The Bi-LSTM architecture aims to create a data-efficient recommendation system. Deep learning in recommendation is not new, but applying it to E-commerce is. The study uses AlexNet, ResNet-50, and Google Net pre-trained CNN architectures.

### 3.3 CNN for extraction of feature attributes

CNN is utilized to extract the top-notch features of the product attribute from input data. Based on the performance of the model and to reduce computational complexity, the various CNN architectures such as ResNet-50, AlexNet, and Google Net are adopted on the Health-product dataset and Flipkart product dataset. For an input attribute that has an area of $224 \times 224$ in channels based on three colors. The output is obtained as feature maps based on the CNN (trained) and it is denoted as $F_{t_i} \in R^{D\times 7\times 7}$ and $F_{b_j} \in R^{D\times 7\times 7}$ in that the dimensional size of the output is denoted as $D$ and the size of the feature map is denoted as $7 \times 7$. The visuals based on feature maps are compressed by $F_{t_i}$ and $F_{b_j}$ to gather dimensional vectors. The vectors based on the dimensions are denoted as $v_{t_i} = \{V_1^{t_i}, V_2^{t_i}, \dots, V_{49}^{t_i}\}$ and $v_{b_j} = \{V_1^{t_i}, V_2^{t_i}, \dots, V_{49}^{t_i}\}$ where the number of features represent in to feature map is denoted as $V \in R^D$. The vectors $t_i$ and $b_j$ is gained by contributing $v_{t_i}$ and $v_{b_j}$ in the layer of pooling. It can be mathematically represented in the Eq. (1).

$$v_{t_i} = \frac{1}{49}\sum_{n=1}^{49} V_n^{t_i}, v_{b_j} = \frac{1}{49}\sum_{n=1}^{49} V_n^{b_j} \dots \quad (1)$$

Where the features utilized for embedding $t_i$ and $b_j$ is denoted as $v_{t_i}, v_{b_j} \in R^D$ .

### 3.4 Tuning the pre-trained CNN

The pre-trained architectures such as AlexNet, Google Net, and ResNet-50 are generally not utilized in an attribute-specific recommendation system for products. Varied kinds of health products typically exhibit different distributions of features. The model will have to pay attention to various qualities when handling various product types as a result of this. Create a second item classification challenge that uses cross-entropy loss to tweak the pre-trained CNN module and build a more discriminative and category-sensitive item embedding that will help guide the next attribute extraction technique. The pre-trained CNN model is altered using Eq. (2).

$$\hat{y}\ item = softmax\left(W^{cat}V_{item}^{gl} + b^{cat}\right),$$
$$L_{category} = \sum_{item\in T\cup B} y_{item}\log(\hat{y}\ item) \ . \quad (2)$$

Where the weight and the bias of the classifier are denoted as $W^{cat}$ and $b^{cat}$ , the probability for predicting the items is referred as $\hat{y}\ item$ and the ground truth value of each item is denoted as $y_{item}$.

### 3.5 Attribute specific representation extraction

E-commerce product descriptions include text and images. This shows shape, pattern, and style. A CNN-Bi-LSTM is advised for meaningful attribute-specific region localization and representation building utilizing a predetermined item with weak supervision. Feature set A. Previous attribute-aware algorithms acquired universal representations for every attribute and item representations using attribute combinatoriality. Because each object has distinct attributes, fixed attribute representations are not flexible enough. Each item can have its own attribute representation in the attribute-specific recommendation system for the pattern attribute of a

Received: June 16, 2023. Revised: August 30, 2023. 

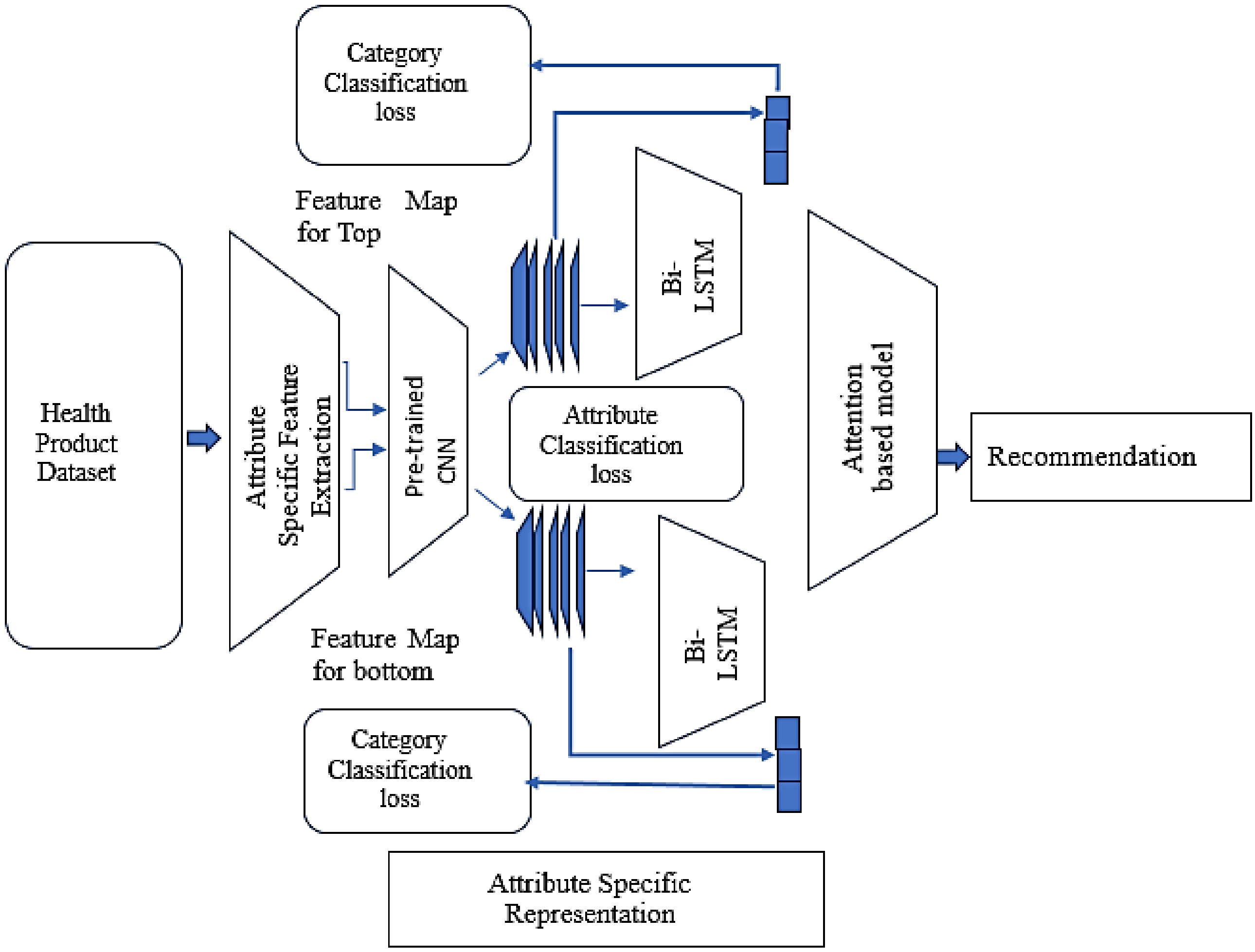


Figure. 2 Process in attribute specific representation extraction for health product recommender system

product ak, which is learned in an attribute-specific feature space. Fig. 2 shows the steps of attribute-specific representation extraction for health product recommender systems.

- Data preprocessing: For modelling, data must be cleansed and prepared. This may involve selecting features, eliminating outliers, and normalising data.
- Attribute-specific feature extraction: This involves extracting relevant features for each attribute of the product, such as its ingredients, nutrition facts, or price. For example, for a health product recommender system, one may want to extract the nutritional value of the product, its intended use, and any potential allergens.
- Attribute-specific representation learning: This step involves learning representations for each attribute of the product. Recurrent neural networks and convolutional neural networks are two deep learning models that can be used for this. The goal is to learn a brief depiction of the main aspects of each quality.
- Integration of attribute representations: This step involves combining the representations learned for each attribute to generate a single representation for the entire product. This can be done using simple techniques such as concatenation or more complex techniques such as attention-based models.
- Recommendation: Once the representations for each product have been generated, a recommendation algorithm can be used to suggest products users based on their preferences.

$F \in R^{D\times7\times7}$ is known as the extracted feature map among the attributes of a specific block. The features consist of $K$ blocks present in Bi-LSTM that relate with $K$ attributes of health products and their descriptions. An independent convolutional layer is adjusted for $k$th attribute for the dimensional size of $D \times 1 \times 1$ which is utilized to select the feature map $F\ to\ F'_k \in\ R^{D\times7\times7}$ and the unique parameters are provided for the attribute blocks. For $t_i$ and $b_j$, the representations of the attribute $k$ obtained from Bi-

LSTM are designated into the matrix form of $K \times D$. The matrix form of the $k$ attribute is represented in Eq. (3).

$$A_{t_i} = [a_1^{t_i}, a_2^{t_i}, \dots, a_K^{t_i}] \text{ and } A_{b_j} = [a_1^{b_j}, a_2^{b_j}, \dots, a_K^{b_j}] \quad \dots\dots \tag{3}$$

Where $A_{t_i}$ and $A_{b_j}$ represents the feature matrix of two attributes $t_i$ and $b_j$ respectively.

The optimization is directly performed for $a_k$ among $A_{t_i}$ and $A_{b_j}$ based on tasks of matching the products. A task based on prediction is assigned in the layer of CNN to provide attribute recommendations. To an individual attribute, the value based on ground truth is assigned, for example, the attribute is selected as color and the value is provided as white. For an attribute value of $K$, $N^k$ possible values are selected to label the values on $item \in T \cup B$. The equation for predicting the value of attributes including the entropy loss is represented in Eq. (4).

$$\hat{z}_k^{item} = softmax(W_k^{attr} a_k^{item} + b_k^{attr}), \quad L_{attribute} = -\sum_{item \in T \cup B} \sum_{k=1}^{k} z_k^{item} \log\left(\hat{z}_k^{item}\right) \tag{4}$$

Where the weight and bias of the corresponding classifier in the $k$th attribute are represented as $W_k^{attr} \in R^{K \times D}$ and $b_k^{attr} \in R^{N^k}$. The estimated probability of the item for the probable attribute$a^k$ values are represented as $\hat{z}_k^{item} \in R^{N^k}$. The optimization is performed for $L_{attribute}$ for every individual block to reflect the quality of the item targeted in $k$th attribute.

### 3.6 Attention for product attributes in descending order (ratings)

In general, most individuals prefer various combinations to choose health products. When the person needs to select a body weight gainer, they may think about the medical composition and complexity of the product. To make it simple, a rating mechanism in descending order is proposed for the product attributes which helps users to choose the best among the recommended products. The representation attribute for the $t_i$ is denoted as $a_k^{t_i} \in A_{t_i}$ and the score $s_k^{t^i}$ based on attention is utilized to specify the significance of the negative rating $b_j$ which is represented in the following Eq. (5).

$$s_k^{t^i} = W \tanh(w_1 a_k^{t^i} + w_2 v_{b_j}^{global}) \tag{5}$$

Where the weight of projection is denoted as $W$ and the weighted matrix is denoted as $w_1 \in R^{D \times D}$ and $w_2 \in R^{D \times D}$. The ratings based on weight $\beta_k^{t_i}$ for the attribute of $t_i$ is calculated using Eq. (6) represented below,

$$\beta_k^{t_i} = \frac{\exp(s_k^{t_i})}{\sum_{k=1}^{K} \exp(s_k^{t_i})} \tag{6}$$

The attribute based on ratings of the vector $V_{t_i}^{attn} = \left[\beta_1^{t_i}, \beta_2^{t_i}, \dots, \beta_K^{t_i}\right] \in R^K$, where the $k$th attribute of the lower attribute $b_j$is represented as $k$th dimension of $V_{t_i}^{attn}$. similarly, score attributes based on $b_j$ attention is represented in Eq. (7).

$$s_k^{b_j} = V_{attn} \tanh(w_1 a_k^{b_j} + w_2 v_{t_i}^{global}) \tag{7}$$

The ratings are based on vector for the attribute of $t_i$is calculated using Eq. (8) is represented below

$$\beta_k^{b_j} = \frac{\exp(s_k^{b_j})}{\sum_{k=1}^{K} \exp(s_k^{b_j})} \tag{8}$$

$$V_{b_j}^{attn} = \left[\beta_1^{b_j}, \beta_2^{b_j}, \dots, \beta_K^{b_j}\right] \in R^K \tag{9}$$

The representations based on product attributes $t_i$ and $b_j$ is vectored as $V_{t_i}^{attn}$ and $V_{b_j}^{attn}$, that are conditions among themselves.

### 3.7 Attribute model based on compatibility

The attribute representation such as $A_{t_i}$ and $A_{b_j}$ are utilized to achieve prediction for pairs in a compatible manner. For every product pair $t_i$ and $b_j$, a linear transformation is performed for different categories of health products. The attribute-wise descending compatibility model is represented in Fig. 3.

The matrix $M_{ij}^{compat} \in R^{K \times K}$ is known as a compatible matrix which is utilized in computing the score of affinity among every pair of representations $\left(a_k^{t_i}, a_k^{b_j}\right)$. The effective calculation can be performed using Eq. (10) mentioned below,

$$M_{ij}^{compat} = (A_{t_i} W^{c_i c_j}) W^{compat} (A_{b_j} W^{c_i c_j}) \in R^{K \times K} \tag{10}$$

Where the category of the specified weight matrix

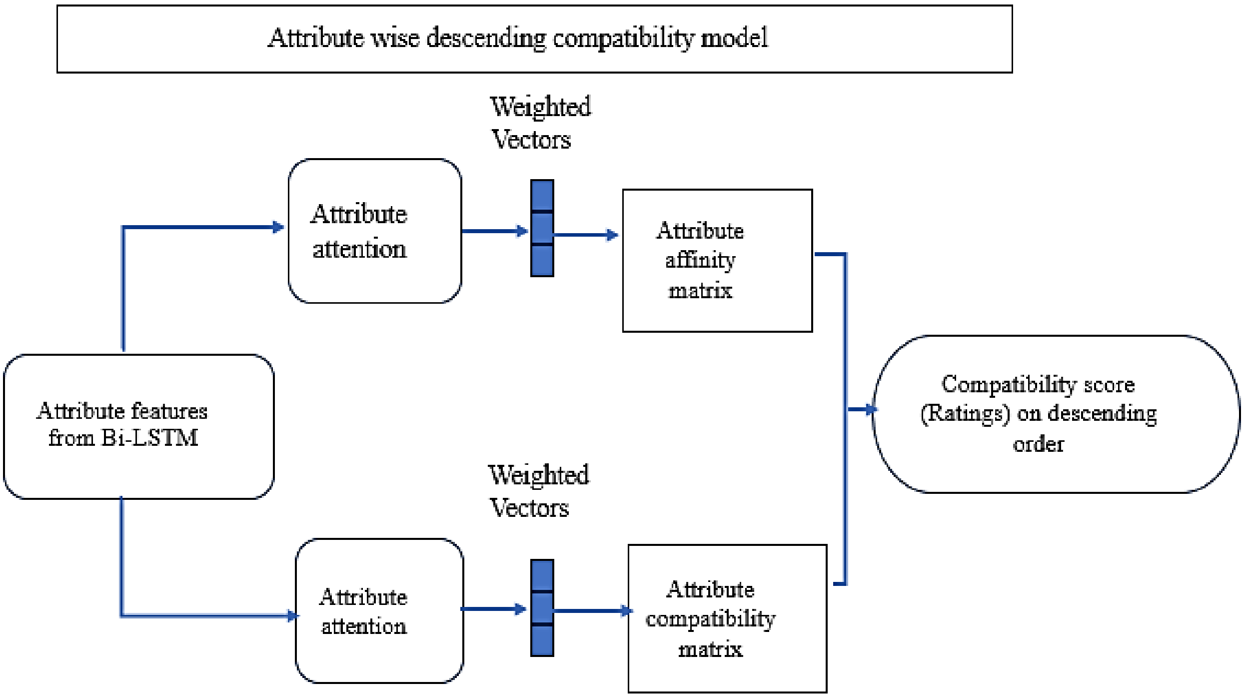


Figure. 3 Attribute-wise descending compatibility model

is represented as $W^{c_i c_j}$, in that $c_i c_j$ represents categorized labels of positive and negative rating products. The features spaces for the attribute-based transformation matrix are represented as $W^{compat}$. An individual element present in $M_{ij}^{compat}$ results in the dot product among the pair of attribute representation $a_k^{t_i}$ and $a_k^{b_j}$, moreover, the attribute pair is utilized to inherent the score based on compatibility. To match products, two attributes must be highly associated and often bound. A higher score indicates this. The product among two vectors for a pairwise combination is represented in Eq. (11).

$$M_{ij}^{affinity} = v_{t_i}^{attn} \otimes v_{b_j}^{attn} \in R^{K \times K} \tag{11}$$

Where $\otimes$ is known as the operator to perform outer product and the matrix for the affinity value for a large component is denoted as $m_{kk'}^{affinity} \in M_{ij}^{affinity}$, which performs using the attributes of $a_k$ and $a_k{}'$ based on high scores of affinity.

The compatibility score of the weighted matrix for a product pair is obtained by the Eq. (12) represented below,

$$M_{ij}^{weighted\ compatibility} = M_{ij}^{affinity} \odot M_{ij}^{compat} \in R^{K \times K} \tag{12}$$

Where the operator for element for element-wise multiplication is represented as $\odot$. By performing multiplication in elemental order, a large score is obtained when the values of $m_{kk'}^{compact}$ and $m_{kk'}^{affinity}$ are high. In large $m_{kk'}$, the attributes of $a_k$ and $a_k{}'$ are complement each other and $t_i$ and $b_j$ tends to perform ideally on the attributes of $a_k$ and $a_k{}'$ respectively.

In this approach, the attribute compatibility model gives a clear description of which pairings of traits are most important and have the most effects on the outfit, either positively or negatively. Additionally, there is a greater likelihood of increasing recommendation accuracy by combining fine-grained attribute-level affinity since the complementary data from various attribute views provides stronger signals for identifying related products. The final score of compatibility among $t_i$ *and* $\hat{y}_{ij}^{compat}$ is obtained by the addition of elements present in $M_{ij}^{weighted\ compatibility}$ is represented in Eq. (13).

$$\hat{y}_{ij}^{compat} = \sum_{K=1}^{K} \sum_{K'=1}^{K} m_{kk'} \in M_{ij}^{weighted\ compatibility} \tag{13}$$

### 3.8 Evaluation of ranking loss function

There are only positive ratings of a product present in the dataset, whereas the negative ratings are undetected. Thus the ranking loss function based is utilized to exhibit the relation among the pair of positive rating $t_i$ and negative rating $b_j$. Moreover, the ranking loss function creates pair of positive and

Table 1. Performance of various CNN architectures for health-product dataset

| Dataset | CNN Models | Sensitivity (%) | Precision (%) | AUC (%) | Hit rate (%) |
|---|---|---|---|---|---|
| Health-product dataset | Bi-LSTM | 86.24 | 83.21 | 79 | 18.24 |
| | Alex-Net | 80.05 | 87.74 | 84 | 17.53 |
| | Google-Net | 81.17 | 86.93 | 87 | 19.87 |
| | ResNet-50 | 84.64 | 89.17 | 91 | 20.32 |
| | Alex-Net-Bi LSTM | 82.44 | 89.88 | 84.62 | 18.34 |
| | Google Net- Bi LSTM | 83.92 | 89.59 | 88.5 | 20.27 |
| | ResNet-50 – Bi LSTM | 85.95 | 90.86 | 93 | 21.65 |

negative ratings for each product corrupted $(t_i, b_{j'})$ and $(t_{i'}, b_j)$ by exchanging unnoticed positive and negative ratings. So, the noticed pair must be given priority at on higher rate than the unnoticed one, it is represented in Eq. (14) shown below,

$$L_{rl} = -\sum_{(i,j,j')\in D} \ln\left(\sigma\left(\hat{y}_{ij}^{compat} - \hat{y}_{ij'}^{compat}\right)\right) \quad (14)$$

Where all training samples are represented as $D$ and the sigmoid function is denoted as $\sigma$.

Finally, by using Eqs. (2), (4), and (14), the objective function of the Attribute specific recommendation system for health products is formulated using Eq. (15).

$$L = L_{category} + L_{attribute} + L_{rl} \quad (15)$$

## 4. Results and empirical analysis

This section provides the results of the proposed CNN-Bi-LSTM model for a recommendation of Health products with various recommendation models described in related works. The design and simulation of the CNN-Bi-LSTM are performed using PyTorch with NVIDIA GTX 2080 Ti and the system is operated with 8GB RAM and i5 processor. The CNN-Bi-LSTM is used to recommend health products based on user preferences. There are two datasets utilized to evaluate CNN-Bi-LSTM, the datasets include the health-product dataset and the Flipkart product dataset. The data is separated as training data and testing data in the ratio of 80:20. The performance of the CNN-Bi-LSTM is evaluated using precision, sensitivity, area under curve (AUC), and hit rate (HR) that is evaluated using the formulas represented in Eqs. (16-19).

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (16)$$

$$Sensitivity = \frac{TP}{(TP+FN)} \times 100 \quad (17)$$

$$Area\ Under\ Curve\ (AUC) = \frac{\sum pred_{pos} > pred_{neg}}{N_{pos} \times N_{neg}} \quad (18)$$

$$Hit\ Rate = \frac{no.of.hits}{|D_{test}|} \quad (19)$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 10 \quad (20)$$

Where the collection of all Test cases is represented as $D_{test}$, true positive as $TP$, false positive as $FP$, and false negative as $FN$.

### 4.1 Performance analysis

The performance of the health-product dataset and Flipkart product dataset is described in this section. The performance is evaluated based on the parameters such as sensitivity, precision, AUC, and hit rate. The performance is evaluated for the various CNN architectures such as Bi-LSTM, AlexNet, Google Net, ResNet-50, AlexNet-Bi LSTM, GoogleNet-Bi LSTM, and ResNet-50--Bi LSTM. The below Table.1 represents the performance of the datasets such as the health-product dataset and Flipkart product dataset.

In the above Table 1, the performance of the various CNN architectures is discussed by computing the based on the parameters like sensitivity, precision, AUC, and hit rate. The results were obtained from the Table 1 shows that the ResNet LSTM attained a high rate of sensitivity, precision, and AUC of 85.95%, 90.86%, and 88.5% respectively for the Health-product dataset. Further, the average hit rate of the CNN-Bi-LSTM method for both datasets is performed well than other architectures. The graphical comparison of various CNN architectures is represented in the Fig. 4.

Table 2. Performance of various CNN architectures for Flipkart product dataset

| Dataset | CNN Models | Sensitivity (%) | Precision (%) | AUC (%) | Hit rate (%) |
|---|---|---|---|---|---|
| Flipkart product dataset | Bi- LSTM | 84.97 | 82.13 | 76 | 16.43 |
| | Alex-Net | 79.54 | 84.47 | 82 | 15.53 |
| | Google-Net | 80.47 | 85.39 | 85 | 17.46 |
| | ResNet-50 | 82.46 | 87.19 | 89 | 18.24 |
| | Alex-Net-Bi LSTM | 81.45 | 88.45 | 82.26 | 16.59 |
| | Google Net- Bi LSTM | 82.25 | 88.56 | 86.34 | 18.13 |
| | ResNet-50– Bi LSTM | 85.42 | 89.12 | 91.11 | 19.59 |

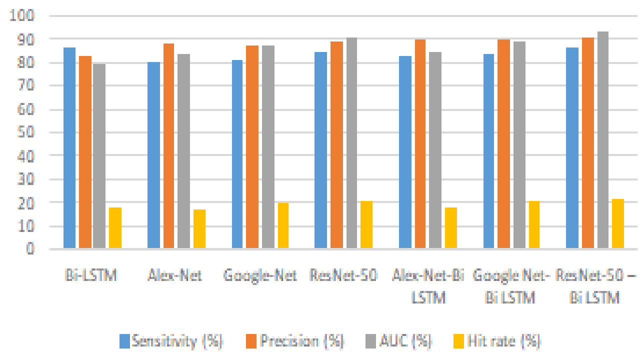


Figure. 4 Graphical representation of performance of different CNN models for the health-product dataset

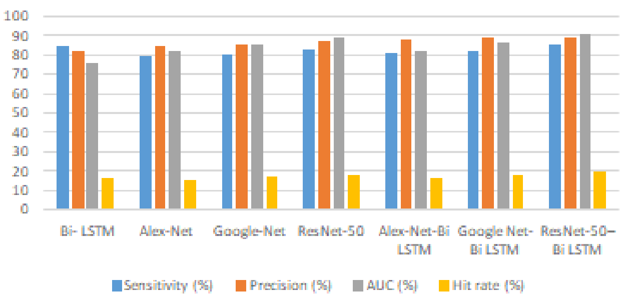


Figure. 5 Graphical representation of the performance of different CNN models for the Flipkart product dataset

Table 3. Comparison of CNN-Bi-LSTM with existing classifiers models

| Classifiers | Accuracy (%) | Recall (%) | User coverage (%) |
|---|---|---|---|
| W-RNN [5] | 91.46 | 82.53 | 87.63 |
| Improved SVM [4] | 92.7 | 86.25 | 84.29 |
| CNN-Bi-LSTM | **95.52** | **88.31** | **89.51** |

In Table 2, the performance of the various CNN architectures is discussed by computing the based on the parameters like sensitivity, precision, AUC, and hit rate. The results were obtained from the Table 2 shows that the ResNet-Bi LSTM attained a high rate of sensitivity, precision, and AUC of 85.42%, 89.12%, and 99.11% respectively for the Flipkart product dataset. Further, the average hit rate of the CNN-Bi-LSTM method for both datasets is performed well than other architectures.

The graphical comparison of various CNN architectures using the Flipkart product dataset is represented in the Fig. 5.

### 4.2 Comparative analysis

This section provides a comparison among various classifiers such as W-RNN [5], improved SVM [4], and proposed CNN-Bi LSTM. The values of Accuracy, Recall, and User Coverage are evaluated based on the overall performance of the classifiers. The results obtained from the comparison show that the proposed CNN-Bi-LSTM achieved better performance in accuracy, recall, and user coverage. The graphical representation of CNN-Bi-LSTM with existing classifiers is represented in Fig. 6. The obtained comparative results are shown in below Table 3 represented as follows:

This paper proposes a CNN-Bi-LSTM-based E-commerce-based personalized health product recommendation system. Despite mentioning the dataset's size and origin, the data description is lacking. Amazon's health-product dataset has 20,726 reviews and ratings, and Flipkart's has 21,889 healthcare product entries with crucial features. For result validity and reproducibility, data distribution, preprocessing, and potential biases must be disclosed. W-RNN and Improved SVM, two relevant and successful health product recommendation algorithms, are compared to CNN-Bi-LSTM. W-RNN's capacity to handle sequential data and time-dependent patterns is essential for modeling user behavior over time, while Improved SVM's multi-class categorization suits varied health product

Received: June 16, 2023. Revised: August 30, 2023. 

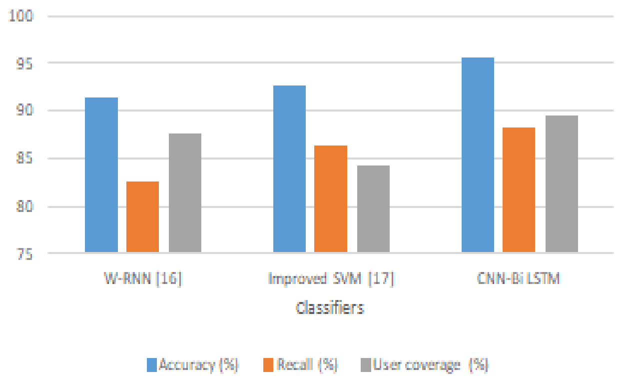


Figure. 6 Comparison of CNN-Bi-LSTM with existing classifiers

categories and user preferences. CNN-Bi-LSTM outperforms W-RNN and Improved SVM in accuracy, recall, and user coverage metrics for personalized health product recommendations.

## 5. Conclusion

Our CNN-Bi-LSTM-based E-commerce-based personalized health product recommendation system is new and successful. We used pre-trained CNN-based transfer learning models and attribute-specific representation extraction to overcome the constraints of methods that rely on latent natural language features and pre-defined attributes. Our CNN-Bi-LSTM model outperforms W-RNN and improved SVM on the health-product dataset and Flipkart health product dataset. Our recommendation algorithm now provides accurate and relevant individualized health product recommendations. Our recommendation algorithm outperforms others due to its high AUC and hit rate. Despite encouraging results, our CNN-Bi-LSTM model has room for improvement. To improve suggestion accuracy and user preferences, we can integrate new data sources, such as user behavior and social interactions. Enhancing transfer learning models or fine-tuning them can improve system performance.

Investigating explainability strategies to provide extensive explanations for recommended health goods could boost user engagement and trust in the system. Transparency and interpretability are crucial for tailored health advice that can affect people's health. Real-world user studies and feedback on personalized health product recommendations can help us understand the system's efficacy and improve it.

## Notations lists

| Notation | Meaning |
|---|---|
| $v_{t_i}$ | Feature vector item |
| $v_{b_j}$ | Feature vector product |
| $\hat{y}\ item$ | Atomic attribute item extraction using CNN |
| $L_{category}$ | Atomic attribute classification item extraction using CNN and cross-entropy |
| $A_{t_i}$ | Attribute specific item extraction using Bi-LSTM |
| $A_{b_j}$ | Attribute specific product extraction using Bi-LSTM |
| $\hat{z}_k^{item}$ | Attribute item prediction using CNN-Bi-LSTM |
| $L_{attribute}$ | Attribute prediction class using CNN-Bi-LSTM entropy loss |
| $\beta_k^{t_i}$ | Attribute vector rating for item |
| $\beta_k^{b_j}$ | Attribute vector rating for product |
| $M_{ij}^{compat}$ | compatible matrix |
| $M_{ij}^{affinity}$ | Product of the affinity matrix |
| $\left(a_k^{t_i}, a_k^{b_j}\right).$ | Affinity matrix |
| $M_{ij}^{weighted\ compatibility}$ | The weighted compatibility matrix |
| $L_{rl}$ | Ranking loss function |

## Conflicts of interest (Mandatory)

The authors affirm that they are aware of no personal or financial conflicts of interest that might have affected the research described in this paper.

## Author contributions (Mandatory)

B Ramakantha Reddy conceptualization, data curation formal analysis, methodology, software writing, original draft, investigation, resources.

R. Lokesh Kumar writing—review and editing, visualization, supervision, project administration.

## References

[1] L. Liu, I. Silva, P. Nogueira, A. Magalhães, and E. Martins, "User Aesthetics Identification for Fashion Recommendations", *Recommender Systems in Fashion and Retail, Springer Lecture notes in Electrical Engineering*, pp. 41-55, 2021.

[2] B. Li, J. Li, and X. Ou, "Hybrid recommendation algorithm of cross-border e-commerce items based on artificial intelligence and multi view collaborative fusion", *Journal of Neural Computing and Applications*, Vol. 34, No. 9, pp. 6753-6762, 2022.

[3] S. Nair, K Patil, H. Waghela, and S. Pansambal, "Outfit Recommendation–Using Image

Processing", *Journal of Algebraic Statistics*, Vol. 13, No. 2, pp. 1699-1706, 2022.

[4] Z. Wang, X. Tao, X. Zeng, Y. Xing, Y. Xu, Z. Xu, P. Bruniaux, and J. Wang, "An Interactive Personalized Garment Design Recommendation System Using Intelligent Techniques", *Applied Sciences*, Vol. 12, No. 9, pp. 46-54, 2022.

[5] L. Zhou, "Product Advertising Recommendation in E-Commerce based on Deep Learning and Distributed Expression", *Journal of Electronic Commerce Research*, Vol. 20, No. 2, pp. 321-342, 2020.

[6] X Chen, C. Lei, D. Liu, G. Wang, H. Tang, Z. Zha, and H Li, "E-Commerce Storytelling Recommendation using Attentional Domain-Transfer Network and Adversarial Pre-training", *IEEE Transactions on Multimedia*, Vol. 24, pp. 506-518, 2021.

[7] G. H. Lee, S. Kim, and C. K. Park, "Development of Fashion Recommendation System using Collaborative Deep Learning", *International Journal of Clothing Science and Technology*, Vol. 34 No. 5, pp. 732-744, 2022.

[8] V. Atina and D. Hartanti, "Knowledge Based Recommendation Modeling for Clothing Product Selection Recommendation System", *Journal Teknik Informatika (JUTIF)*, Vol. 3, No. 5, pp. 1407-1413, 2022.

[9] Y. Yuan, M. Park, and J. Huh, "A Proposal for Clothing Size Recommendation System Using Chinese Online Shopping Malls: The New Era of Data", *Applied Sciences*, Vol. 11, No. 23, p. 11215, 2021.

[10] L. D. Divitiis, F. Becattini, C. Baecchi, and A. D. Bimbo, "Disentangling Features for Fashion Recommendation", *ACM Transactions on Multimedia Computing, Communications, and Applications*, Vol. 19, No. 1, pp. 1–21, 2023.

[11] C. Yan, Y. Chen, and L. Zhou., "Differentiated Fashion Recommendation using Knowledge Graph and Data Augmentation", *IEEE Access*, Vol. 7, pp. 102239-102248, 2019.

[12] Y. S. Kim, H. Hwangbo, H. J. Lee, and W. S. Lee, "Sequence-aware Recommenders for Fashion E-commerce", *Electronic Commerce Research*, Vol. 1325, pp. 1-21, 2022.

[13] T. Zhu, Y. Wang, H. Li, Y. Wu, X. He, and B. Zhou, "Multimodal joint attribute prediction and value extraction for e-commerce product", *arXiv preprint arXiv:2009.07162*, 2020.

[14] G. Gao, L. Liu, L. Wang, and Y. Zhang, "Fashion Clothes Matching Scheme Based on Siamese Network and AutoEncoder", *Journal of Multimedia Systems*, Vol. 25, No. 2, pp. 1-10, 2019.

[15] F. Gutiérrez, N. Htun, F. Schlenz, A. Kasimati, and K. Verbert, "A review of Visualisations in Agricultural Decision Support Systems: An HCI perspective", *Computers and Electronics in Agriculture*, Vol. 163, pp. 104-144, 2019.

[16] P. Buche, B. Cuq, J. Fortin, and C. Sipieter, "Expertise-based Decision support for Managing Food Quality in Agri-food companies", *Computers and Electronics in Agriculture*, Vol. 163, pp. 10-13, 2019.

[17] T. C. T. Chen and M. C. Chiu, "Mining the Preferences of Patients for Ubiquitous Clinic Recommendation", *Health Care Management Science*, Vol. 23, pp. 173–184, 2020.

[18] A. K. Sahoo, C. Pradhan, and B. S. P. Mishra, "SVD based Privacy Preserving Recommendation Model using Optimized Hybrid Item-based Collaborative Filtering", In: *Proc. of the 2019 International Conf. on Communication and Signal Processing (ICCSP)*, Chennai, India, pp. 294-298, 2019.

[19] Y. Dai and G. Wang, "A deep inference learning framework for healthcare", *Pattern Recognition Letters*, Vol. 139, pp. 17-25, 2020.

[20] R. Huang, N. Wang, C. Han, F. Yu, and L. Cui, "TNAM: A tag-aware Neural Attention Model for Top-N Recommendation", *Journal of Neurocomputing*, Vol. 385, pp. 1-12, 2020.

[21] C. Kim, Y. Son, and S. Youm, "Chronic Disease Prediction Using Character-Recurrent Neural Network in The Presence of Missing Information", *Applied Sciences*, Vol. 9, No. 10, p. 2170, 2019.

[22] S. D. Lin, T. Y. Chiu, C. Y. Huang, and C. Chang, "Personalized Exercise Recommendation System Based on Recurrent Neural Networks for Health Management", *IEEE Access*, Vol. 7, pp. 62190-62202, 2019.

[23] Y. Liu, J. Feng, and J. Lu, "Collaborative Filtering algorithm based on rating distance", In: *Proc. of the 11th International Conf. on Ubiquitous Information Management and Communication (IMCOM'17)*, Beppu Japan, Vol. 66, pp. 1-7, 2017.

[24] S. Mao and E. Sejdic, "A Review of Recurrent Neural Network-Based Methods in Computational Physiology", *IEEE Transactions on Neural Networks and Learning Systems*, pp. 1-21, 2022.

[25] S. Liu, F. Dong, X. Wei, L. Zhang, and B. Xie, "Personalized Health Product Recommendation System using Recurrent Neural Networks", *Journal of Ambient Intelligence and Humanized Computing*, Vol. 12, No. 9, pp. 9779-9790, 2021.

[26] C. Zhao, J. You, X. Wen, and X. Li, "Deep Bi-

LSTM Networks for Sequential Recommendation”, *Entropy*, Vol. 22, No. 8, 2020.

[27] Z. Zhang, X. Gao, Z. Wang, and Y. Yao, “A CNN-LSTM-based Personalized Recommendation System for Chronic Disease Management”, *Multimedia Tools and Applications*, Vol. 80, No. 23, pp. 35639-35654, 2021.

[28] A. K. Sahoo, C. Pradhan, R. K. Barik and H. Dubey, “DeepRaco: Deep Learning Based Health Recommender System Using Collaborative Filtering”, *Computation*, Vol. 7, No. 2, p. 25, 2019.

[29] T. Wang, Y. Zhang, Y. Zhang, H. Lu, B. Yu, S. Peng, Y. Ma, and D. Li, "A Hybrid Model Based on Deep Convolutional Network for Medical Named Entity Recognition", *Journal of Electrical and Computer Engineering*, Vol. 2023, pp. 1-11, 2023.

[30] B. K. Reddy and D. Delen, “Predicting hospital readmission for lupus patients: An RNN-LSTM-based deep-learning methodology”, *Computers in Biology and Medicine*, Vol. 101, pp. 199-209, 2018.

[31] F. Zeng, R. Tang, and Y. Wang, "User Personalized Recommendation Algorithm Based on GRU Network Model in Social Networks", *Journal of Mobile Information Systems*, Vol. 2022, pp. 1-8, 2022.

[32] L. Chen, G. Chen, and F. Wang, “Recommender Systems based on User Reviews: The state of the art”, *User Modeling and User-Adapted Interaction*, Vol. 25, pp. 99–154, 2015.

[33] S K. Addagarla, and A. Amalanathan, "Probabilistic Unsupervised Machine Learning approach for a Similar Image Recommender System for E-commerce", *Symmetry*, Vol. 12, No. 11, 2020.