Deep Learning Model for Predicting Consumers' Interests of IoT Recommendation System

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***Abstract*—This electronic the Internet of Things (IoT) technology has contributed to several domains such as health, energy, education, transportation, industry, and other domains. However, with the increased number of IoT solutions worldwide, IoT consumers find it difficult to choose the technology that suits their needs. This article describes the design and implementation of an IoT recommendation system based on consumer interests. In particular, the knowledge-based IoT recommendation system exploits a Service Oriented Architecture (SOA) where IoT device and service providers use a registry to advertise their products. Moreover, the proposed model uses a Long Short-term Memory (LSTM) deep learning technique to predict the consumer's interest based on the consumer's data. Then the recommendation system do the mapping between the consumers and the related IoT devices based on the consumer interests. The proposed Knowledge-based IoT recommendation system has been validated using a real-world IoT dataset collected from Twitter Application Programming Interface (API) that include more than 15,791 tweets. Overall the results of our experiment are promising in terms of precision and recall. Furthermore, the proposed model achieved the highest accuracy score compared with other state-of-the-art methods.**

Keywords*—Internet of things; IoT; knowledge-based; recommendation system; service-oriented architecture; SOA; long short-term memory; LSTM; deep learning

I. Introduction

The number of Internet of Things (IoT) devices connected to the internet is growing exponentially. According to statistics [1], the number of devices connected to the internet will keep increasing to reach 19.1 billion devices by the year 2025. IoT technology plays a vital role in improving services provided in several domains such as energy, transportation, food production, water supply, health care, education, and other crucial services [2,3,4,5]. IoT Technology has the capability of solving several issues related to smart grids, warming systems, saving water, increasing smart farms, and are considered to be the main part when it comes to smart cars.

With the accelerated growth in the number of connected IoT devices and the targeted services that the IoT devices are designed for, IoT services' consumers face an issue in choosing the appropriate IoT devices and services that suits their needs [6,7,8,9]. Therefore, novel techniques are required to help IoT services' consumers in choosing the suitable IoT devices and services that makes their life easier and their daily activities more efficient. Traditional techniques presented in the literature that involves recommendations from other consumers or IoT devices and services reputation based on other consumers' ratings might be impractical in this case (i.e., such as collaborative filtering or content-based techniques). For example, let us say consumer x recommended IoT device i to consumer y because it's good in saving energy. However, consumer y misses IoT device t that have more features related to consumer y field which is health (i.e., consumer y is a doctor and more interested in health related gadgets and IoT devices). Knowledge-based techniques can be more beneficial especially when predicting suitable IoT devices and services based on the IoT services' consumers knowledge [10] (i.e., consumer interests are derived from her knowledge).

Consumer interest recognition is becoming an important research problem [11,12]. Consumer interest analysis is the procedure of evaluating, identifying, and understanding the interests, sentiments, qualities, attitudes, and traits of an individual. The consumer interest analysis is beneficial in identifying targeted consumers and improving consumer's service experience. Social media is a good platform for consumer interest analysis where the consumers text, photos, shares, likes, dislikes are used to understand the consumers behavior [13,14,15]. Knowledge-based techniques are used to improve the recommendation process of IoT devices for IoT services' consumers. Hence, this research focuses more on the knowledge of IoT services' consumers by analyzing their tweets from Twitter. Then based on the consumers interests profiling, the knowledge-based recommender system starts the mapping process between the IoT devices registered by IoT device and service providers and the appropriate consumers.

The purpose of this article is to present the design and implementation of a knowledge-based IoT recommendation system architecture to enhance the recommendation of IoT devices and services for users of IoT services. The knowledge-based IoT recommendation system is based on a Service Oriented Architecture (SOA) and a deep learning model to predict the consumer's interest using the consumer's data. The contribution of this work can be outlined as follows:

1) A knowledge-based IoT recommendation system based on SOA is designed and implemented to recommend IoT devices and services to consumers.

2) This study uses a deep learning model called Long Short-term Memory (LSTM) to classify IoT services' consumers based on their interests.

3) The knowledge-based IoT recommendation system is demonstrated using a prototype implementation and experiments using a Twitter API dataset with 15,791 tweets.

The rest of the article is organized as follows: The literature review is discussed in Section II, the design of the knowledge-based recommendation system architecture and the IoT services consumers' interest analysis are presented in Section III, the implementation and experimentation are discussed in Section IV, Section V concludes with some concluding remarks and directions for future work.

II. Literature Review

Several research works have recognized the significance of recommendation systems for IoT environments and discussed different recommendation techniques including: i) content-based, ii) collaborative filtering, iii) knowledge-based, and other techniques [16,17,18,19,20]. Other researchers conducted more specific survey papers on IoT recommendation systems related to the fields of context-aware [21], trust [22], and mobile health (m-health) [23]. Some research works used a content-based technique to recommend IoT devices and services. For example, Frey et al. [24] propose a novel recommendation system that collects IoT related information into inventories from smartphones to facilitate IoT device providers in recommending new personalized IoT devices that are similar to the ones that IoT services consumers are using. In particular, the recommendation system consists of three layers including: i) data gathering from mobile device, ii) building a digital inventory, and iii) creating personalized recommendations. Unlike this research work that neglects the idea of predicting suitable IoT devices and services based on the IoT services' consumers knowledge, a knowledge-based technique is employed when predicting suitable IoT devices and services. In other words, it's more likely that the IoT services' consumers would prefer IoT devices and services that are related to their interest.

Other research works used a collaborative filtering technique to recommend IoT devices and services. For example, Forouzandeh et al. [25] propose an IoT recommendation system based on a collaborative filtering technique. In particular, the system analyzes IoT services consumers' behaviors and uses the Cosine similarity to aggregate the distance between two IoT devices or IoT services consumers. The proposed system architecture consists of three modules including IoT devices, IoT services, and IoT services consumers. Kashef [26] presents an IoT recommendation system based on a clustering technique that overcomes traditional collaborative filtering techniques that suffer from scalability and sparsity issues. In particular, the study compares the performance of several clustering algorithms including k-means, fuzzy c-mean, single-linkage, and self-organization maps. In the evaluation of these clustering algorithms the authors used several datasets including: i) LDOS-CoMoDa (i.e., movie ratings), ii) InCarMusic (i.e., music ratings), iii) Apps in Frappe' (i.e., apps ratings), iv) POI in STS (i.e., rating of places), v) TripAdvisor (i.e., hotel ratings), vi) apple store ratings (i.e., apps ratings), and vii) drug review (i.e., patent reviews on drugs); where the performance of self-organization maps overcomes the other clustering algorithms. Unlike these research works that use collaborative filtering techniques for recommending IoT devices and services and use datasets that are not related to IoT devices and services to evaluate their proposed approaches; A real-world IoT dataset collected from Twitter, which included 15,791 tweets, was used to evaluate our proposed approach of analyzing consumers' interests in IoT services.

Some research works used a hybrid technique to recommend IoT devices and services. For example, Bouazza et al. [27] propose an IoT recommendation system based on a hybrid technique (i.e., collaborative filtering and knowledge-based techniques). In particular, the authors propose to use collaborative filtering and ontology to recommend IoT services that suit IoT services consumers' needs. The proposed ontology namely, Social IoT (SIoT) consists of two different ontologies including social network ontology and IoT ontology. The proposed system uses SIoT ontology to identify the relationship between the IoT services consumer, IoT devices and IoT services to aggregate the IoT services consumer preferences. Moreover, the proposed system determine the top N IoT services based on other IoT services consumer ratings. Yao et al. [28] present a novel framework for recommending things of interest in IoT environments. In particular, the proposed framework is based on a probabilistic matrix factorization model. The model uses three different matrices including: i) user-user relationship matrix, ii) the thing-thing correlation matrix, and iii) the user-thing usage matrix. Unlike these research works that uses ontologies to predict the IoT services' consumers prior knowledge about IoT devices and services, our proposed approach complements these research works by using a deep learning model namely, Long Short-term Memory (LSTM), to classify IoT services' consumers based on their interest and recommend the appropriate IoT devices and services accordingly.

Knowledge-based techniques and IoT technology is used in the literature for recommendations for smart city development and education systems. For example, Xin et al. [29] propose a knowledge-based education recommendation system utilizing IoT technology. In particular, the proposed recommendation system uses an ontology of scientific papers in the field of entrepreneurship (i.e., the authors used it as an example of building an ontology for the education system) and factorization matrix to measure the relevance of users' feedback. Bokolo [30] presents a case-based reasoning recommender system for smart city development (i.e., case-based reasoning is considered as a knowledge-based technique). The main notion of the system is to build a case library which represents a prior experience in the development of smart cities and measure the similarity of the current case with the ones stored in the library. Unlike these research works that use knowledge-based techniques and IoT technology for the recommendations of smart city development and education systems, knowledge-based techniques are used in recommending appropriate IoT devices and services.

IoT technology is also utilized in the literature for context-aware recommendation systems. For example, Cha et al. [31] present an IoT platform for real-time context-aware recommendation. In particular, the architecture of the proposed IoT platform uses a geofencing technique to model the user context-aware based on the location, time and surroundings data collected from IoT users' devices. The proposed IoT platform has been demonstrated using a tourism application. Gyrard and Shetha [32] propose a knowledge-based recommendation system that uses IoT technology for the health-context recommendations. In particular, the proposed system exploits a knowledge repository which consists of linked open datasets and ontologies to recommend alternative medicine for daily discomforts such as fever and headaches. Jabeen et al. [33] present a hybrid-based cardiovascular health recommendation system that uses IoT technology. In particular, the proposed system uses four classifiers including Multi-layer Perceptron (MLP), Support Vector Machines (SVM), Random Forest (RF), and Naive Bayes (NB) for the process of classifying cardiovascular diseases. The classifiers are capable of predicting eight types of cardiovascular diseases (e.g., Hypertension and Acute Coronary Syndrome) using a dataset of cardiovascular diseases. In addition, the proposed system uses collaborative filtering technique for community advice on treatments. Gladence et al. [34] propose a recommendation system for home automation using IoT technology. In particular, the authors use Natural Language Processing (NLP) and voice recognition to help unfortunate people to gain control over IoT devices and the propose system makes recommendations based on the users iterations with the system. Mohamed et al. [35] present a collaborative filtering recommendation system for e-commerce products that uses IoT technology. In particular, the proposed system uses data collected from IoT devices to identify user behavior and other users' feedback on products to make the recommendation of personalized e-commerce products. Unlike these research works that uses IoT technology for recommending products and other context-aware related recommendations such as health related applications, this paper focus on recommending IoT devices and services.

III. Knowledge-Based IoT Recommendation System Architecture

In this paper, a knowledge-based IoT recommendation system architecture is proposed that uses the Service Oriented Architecture (SOA) to deliver IoT devices and services' recommendations based on IoT services consumers' prior knowledge about IoT devices and services. Fig.1 depicts the architecture of our knowledge-based IoT recommendation system which consists of three different layers including: i) the IoT Device and Service Providers Layer, ii) the Knowledge-based IoT Recommendation Layer, and iii) the IoT Services Consumers Layer.

The IoT Device and Service Providers Layer. This layer consists of several IoT device and service providers where IoT devices are provided through shipping companies to IoT services consumers. IoT services are normally provided through web portals and mobile applications. The IoT device and service providers interact with Knowledge-based IoT Recommendation Layer through the IoT Device and Service Registry where they can advertise their IoT devices and services. In order to register the IoT devices and services, the providers need to add the IoT device or service ID, description, and choose an IoT category. In this phase of our work, five different categories are identified for IoT devices and services namely Health, Energy, Education, Transportation, and Industry.

The Knowledge-based IoT Recommendation Layer. This layer consists of eight components including: i) IoT Services Consumers Identity Management (IdM), which is responsible for managing the IoT services consumers identities and require IoT services consumers to register their credentials when they attempt to use the recommender system for the first time, ii) IoT Services Consumers Tweets Collector which is responsible for collecting the IoT services consumers tweets from Twitter API (i.e., this component will be elaborated further in Section 3.1) after requesting their permission to gain access to their Twitter account, iii) Term Frequency–Inverse Document Frequency (TF-IDF) Calculator which is responsible for measuring the terms relevance in the IoT services consumers tweets (i.e., which will be explained in detail in Section 3.2.1), iv) IoT Services Consumers' Interests Analysis which is responsible for identifying the IoT services consumers' interests (i.e., prior knowledge about IoT devices and services, more details about the IoT services consumers' interests identification are presented in Section 3.2.2), v) Categorized IoT Services Consumers is responsible for storing the IoT services consumers categories based on the identified interests (i.e., whether the IoT services consumers interested in IoT devices or services related to the health, energy, education, transportation, or industry domain), vi) IoT Device and Service Registry is responsible for managing the IoT devices and services advertisements where IoT device and service providers are required to register their IoT devices and services by adding the IoT device or service ID, description, and choose an IoT category as aforementioned earlier, vii) Recommendation Handler is responsible for handling IoT device and service recommendation requests from IoT services consumers and recommendation feedbacks, and viii) Recommendation Mapper which is responsible for mapping the recommendations based on the IoT services consumers' category (i.e., based on their interests) and the IoT device and service registered in the IoT Device and Services Registry (i.e., this component will be elaborated further in Section 3.2.3).

The IoT Services Consumers Layer. This layer consists of several IoT services consumers who use IoT devices received from IoT device and service providers through shipping companies. IoT services consumers also use IoT services through web portals and mobile applications. The IoT services consumers interact with Knowledge-based IoT Recommendation Layer through the Recommendation Handler where they can request an IoT device and service recommendation and receive the recommendation feedback. In order for the IoT services consumers to start using the recommender system, they are required to register their credentials first through the IoT Services Consumers Identity Management (IdM).

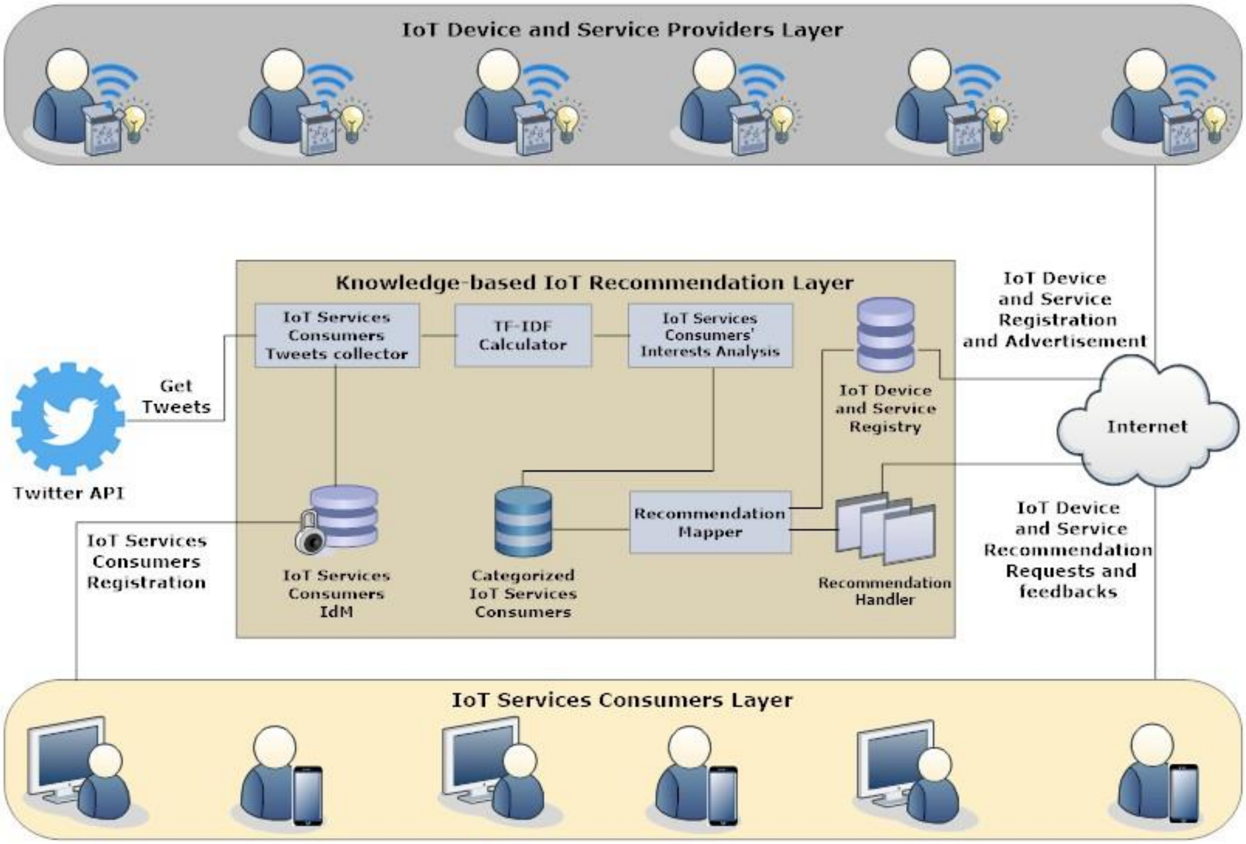


Fig. 1. A Knowledge-based IoT Recommendation System Architecture.

A. *IoT Services Consumers' Tweet Collector*

The IoT Services Consumers' Tweets Collector is used to get the IoT services consumers tweets based on IoT categories. According to several research works the IoT devices and services are applied in several domains including health, energy, education, transportation, and industry [16,17,18,19,20]. Thus, these application domains were used as categories for IoT service consumers' interests. Then, several keywords are used to retrieve tweets related to each IoT proposed interests' category as shown in Table I (i.e., in Section 4.2, the dataset is described in more detail). Then the IoT services consumers' tweets collector uses these keywords to collect the IoT services consumers tweets from Twitter API.

B. *IoT Services Consumers' Interests Analysis*

1) Term Frequency–Inverse Document Frequency (TF-IDF): Term frequency and inverse document frequency (TF-IDF) is a statistic metric used in text mining that determines how relevant a term is to a particular IoT services consumers tweet comparing with all IoT services consumers tweets. TF-IDF assigns two scores to each word in an IoT services consumers' tweets: term frequency (TF) and inverse document frequency (IDF). IDF calculates a word's inverse document frequency, whereas TF calculates the number of times a term appears in an IoT services consumers' tweets. In this paper, the TF-IDF is computed for the most frequent K vocabularies for all posts for the purpose of modeling different terms. Each IoT services consumers tweet has a K-word dictionary reflecting the importance of each term, and the value is 0 if the term does not appear in the IoT services consumers' tweets. A matrix of K×N can be constructed as the input of LSTM model (see Section 3.2.2) based on the corresponding K-word TF-IDF dictionary. The TF-IDF weight of that sentence is computed by multiplying the two scores [36].

TABLE I. THE IOT PROPOSED INTERESTS' CATEGORIES AND RELEVANT KEYWORDS

IoT	Keywords
Energy	Energy Consumption Energy Conservation Energy Technologies
Health	Health Technologies Wearable Technologies Digital Health Health Informatics
Industry	Industry Technologies Smart Industry Industry Solutions
Transportation	Transportation Solutions Smart Transportation Transportation Technologies
Education	Smart Classrooms Education Technology Education Automation

Where TF-IDF denotes the importance of a phrase in an IoT services consumers' tweet. The higher the TF-IDF weight score, the more significant the term in the IoT services consumers' tweets. The suggested model extracts and models different terms in our dataset using the TF-IDF measure. The following equations (1) and (2) can be used to compute TF and IDF of terms:

$$\text{TF(t)} = \frac{Number\ of\ times\ word\ appear\ in\ documents}{Total\ number\ of\ words\ in\ documents} \quad (1)$$

$$\text{IDF} = log\, \frac{Total\ number\ of\ documents}{Frequency\ of\ word\ in\ all\ documents} \quad (2)$$

Here, the TF-IDF value is computed by making a product of the two statistics which means the weight of the words as in Equation (3):

$$\text{TF- IDF(t)} = TF(t)\ *\ IDF(t) \quad (3)$$

TF-IDF is used in this study because it provides a vector representation of the IoT services consumers tweets. The next step is to analyze the IoT services consumers' interests after computing the TF-IDF for our dataset.

2) IoT Services consumers' interests classification using LSTM model: The LSTM model is a powerful deep learning algorithm that produces excellent results and has been applied to several text classification tasks [37, 38, 39, 40]. Our study employs a LSTM model to learn high-level discriminative representations and to identify the IoT services consumers' interests across several categories, including education, energy, health, industry, transportation, and others. Using TF-IDF to extract input representations, the structure of LSTM is expressed in the following manner:

$$i_t = \sigma\,(W_i\,.\,[h_{t-1}, x_t] +\ b_i) \quad (4)$$

$$f_t = \sigma\left(W_f\,.\,[h_{t-1}, x_t] +\ b_f\right) \quad (5)$$

$$o_t = \sigma\,(W_o\,.\,[h_{t-1}, x_t] +\ b_o) \quad (6)$$

$$c_t = f_t \odot c_{t-1} +\ t_i \odot\ \tan h\,(W_c\,.\,[h_{t-1}, x_t] +\ b_c) \quad (7)$$

$$h_t = o_t \odot\ \tan h\,(c_t) \quad (8)$$

i_t, f_t, o_t and c_t are the input gate, forget gate, output gate, and cell input vector respectively. The last hidden state is $h_{[t-1]}$, the current input is x_t, the weighted matrix is $W\,*$, and the biases are $b\,*$. The σ is a logistic sigmoid function, while the $\tan h$ function is a tangent function. The element-wise product of two vectors is $\odot$.

Our LSTM model has the following configurations. It uses 2000 epochs and a loss function namely mean squared logarithmic error with adam optimizer. The softmax activation function is used in all the input, hidden and output layers. The total number of tunable parameters used in the proposed model are summarized in Table II.

TABLE II. THE DESCRIPTION OF THE PROPOSED LSTM MODEL

Layer (type)	**Output Shape**	**Param #**
Embedding	(None, 25, 50)	1,647,250
Spatial Dropout1d	(None, 25, 50)	0
LSTM	(None, 124)	29,440
Dense	(None, 5)	325
Total params		1,677,015
Trainable params		1,677,015

3) Recommendation mapper algorithm: In the knowledge-based IoT recommendation system, we propose that the Recommendation Mapper is responsible for mapping the recommendations based on the IoT services consumers' category $\tau(c)$ and the IoT device (i) or IoT service (i) that has the same IoT device and services category $\tau(i)$ which are registered in the IoT Device and Services Registry R_i. Then the Recommendation Mapper starts the mapping process and updates the recommendation table $\mu(c)$ and present the recommendation m to the IoT services consumers c. Algorithm 1 shows the brief process of the Recommendation Mapper.

Algorithm 1 Recommendation Mapper Algorithm

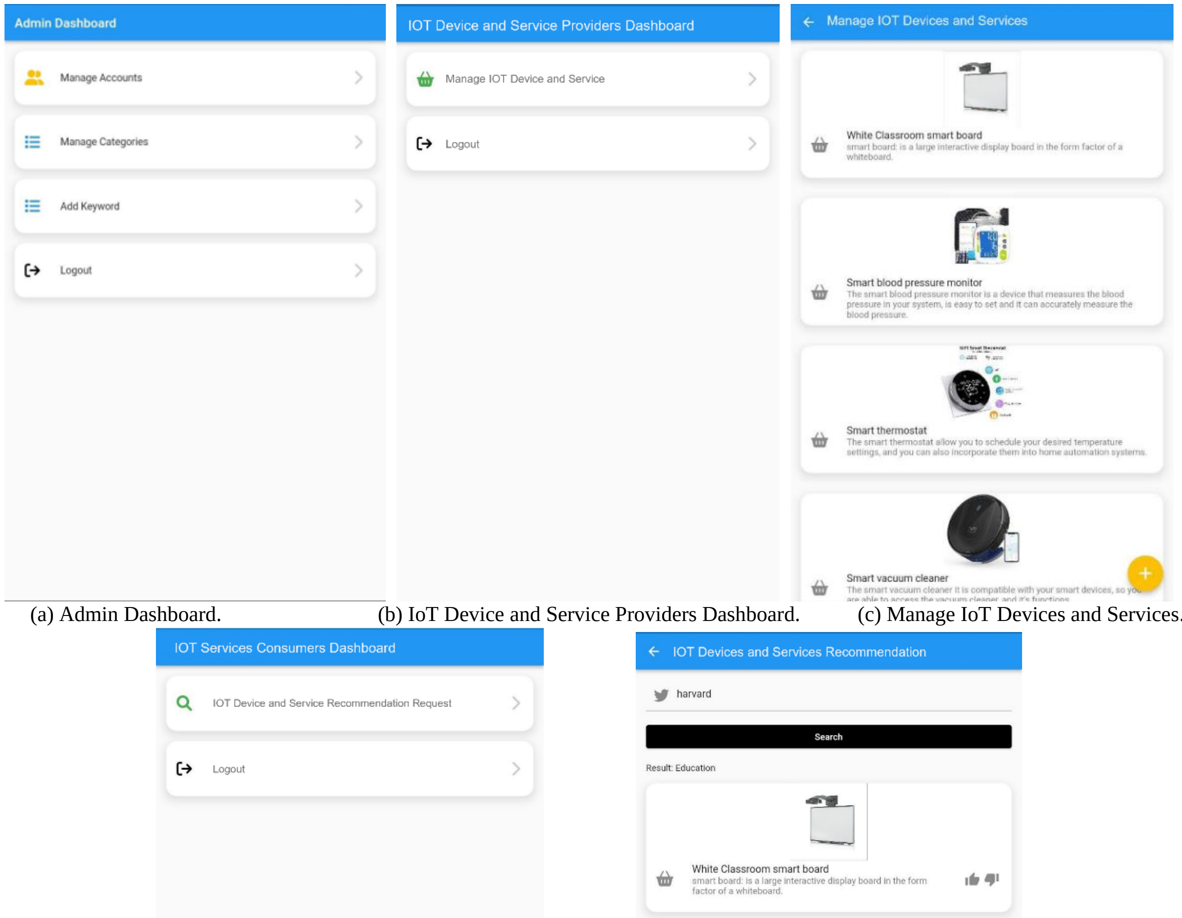
1. **Initialization:** Compute $TF - IDF(t) \in C(t)$ if any
2. **Prediction:** Compute $i_t, f_t, o_t, and\ h_t \in C(t)$ to predict $\tau(c)$
3. **Mapping:** Check R_i
if $d(i)\ or\ s(i) \in \tau\,(i) = \tau\,(c)$ **then**
  Update $\mu(c)$
else
  Notify c "There are no recommended IoT devices or services at the moment, please try again later."
end if
4. **Recommendation:** Get $m \in \mu\,(c)$
for each $m \in \mu\,(c)$
  Present $m\ to\ c$
end for

IV. IMPLEMENTATION AND EXPERIMENTATION

This section describes the knowledge-based IoT recommendation system for evaluating the IoT services consumers' interest classification model collected using Twitter API. Second, we explain the dataset that we have collected using Twitter API to evaluate the IoT services consumers' interest classification model. Finally, the results of the empirical experimentation are discussed to validate the performance of the classification model for IoT services consumers' interests.

A. System Implementation

The implementation of the knowledge-based IoT recommendation system is developed using Flutter 3.0.2 for the mobile application's Graphical User Interfaces (GUIs) to enable IoT device and service registration and advertisement, as well as, IoT device and service recommendation requests and feedbacks. PHP 8.1.7 is used for the mobile application backend. Python 3.10.5 is used for the development of the IoT services consumers' interest classification model in the backend. MySQL 8.0.29 for the development of the database.



(a) Admin Dashboard. (b) IoT Device and Service Providers Dashboard. (c) Manage IoT Devices and Services.

(d) IoT Services Consumers Dashboard. (e) IoT Devices and Services Recommendation.

Fig. 2. Knowledge-based IoT Recommendation System's GUIs

The proposed knowledge-based IoT recommendation system uses several GUIs for the Admin, IoT device and service providers, and consumers of IoT services. Fig. 2 illustrates some of the knowledge-based IoT recommendation system GUIs. For example, Fig. 2(a) showcases the admin's dashboard where she can manage the users accounts whether they were IoT device and service providers or IoT services' consumers, manage IoT categories (i.e., as mentioned earlier, the proposed method categorized IoT devices or services into several categories including health, energy, education, transportation, and industry, where the admin can eventually add new categories as required), add keywords related to the IoT categories to enable the IoT services consumers' interests analysis. Fig. 2(b) illustrates the IoT device and service providers dashboard where they can manage their IoT device or service registration and advertisement by adding an ID, name, description, and image for each IoT device or service as shown in Fig. 2(c). Fig. 2(d) showcases the IoT services' consumers' dashboard where they can request IoT device or service recommendation after requesting their permission to gain access to their Twitter account. Fig. 2(e) illustrates the IoT device and service recommendation to the IoT services' consumers which is based on their interests. Moreover, a like/dislike buttons are added to have some feedback from the IoT services' consumers (i.e., this will help us in calculating the True Positives (TPs), False Positives (FPs), False Negatives (FNs), True Negatives (TNs) later on).

B. Data Description

To evaluate the performance of the IoT services consumers' interest analysis which is the core of the proposed knowledge-based IoT recommendation system, a real-world IoT dataset is collected using Twitter Application Programming Interface (API). The dataset was collected from August 2021 until October 2021. It contains around 15,791 distinct tweets and 11,421 users. Fig. 3 displays the number of tweets for each category. After that the following pre-processing was performed on the dataset: (i) lower casing all words; (ii) filtering out all stop-words non-alphabetic characters; and (iii) removing all words that occurred too rarely in the documents. Finally, the labeling process is conducted to annotate tweets for the classification task using LSTM model.

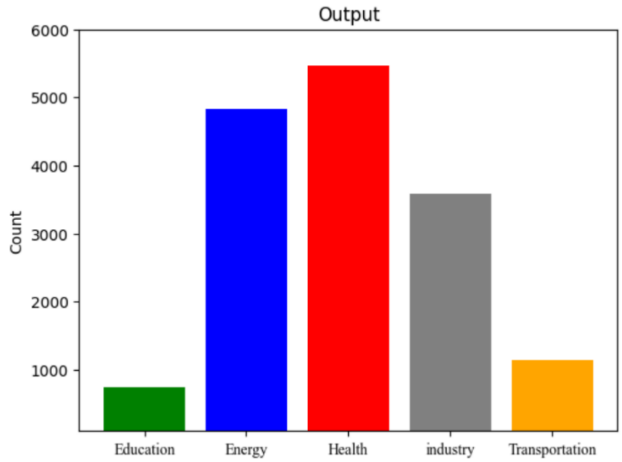


Fig. 3. Data Description.

C. Performance Evaluations

To evaluate the IoT services consumers' classification using LSTM model, we split the dataset into training and testing datasets 70% and 30% respectively. The training dataset includes 12,632 tweets from 7,995 users and the testing dataset includes 3,426 tweets from 3,159 users whereas we divide these users into 5 groups representing the IoT services' consumers interests categories including health, energy, education, transportation, and industry. In the following Section 4.3.1, we describe the evaluation methods used to test our model's performance. We then described the comparison methods in Section 4.3.2. Section 4.4 summarizes the results of our experiments.

1) Evaluations methods: Several well-known evaluation metrics [40] are used including accuracy, precision, recall, and F1-score which are calculated based on the numbers of True Positives (TPs) (i.e., the IoT services consumers' interests classification model predicted positive and it is true), False Positives (FPs) (i.e., the IoT services consumers' interests classification model predicted positive and it is false), False Negatives (FNs) (i.e., the IoT services consumers' interests classification model predicted negative and it is false), True Negatives (TNs) (i.e., the IoT services consumers' interests classification model predicted negative and it is true). These evaluation metrics are calculated as follows:

$$Accuracy = \frac{TPs + TNs}{TPs + FPs + TNs + FNs} \tag{9}$$

$$Precision = \frac{TPs}{TPs + FPs} \tag{10}$$

$$Recall = \frac{TPs}{TPs + FNs} \tag{11}$$

$$\text{F1-Score} = 2 * \left(\frac{Precision * Recall}{Precision + Recall}\right) \tag{12}$$

2) Methods for comparison: The proposed approach was compared with three well-known models:

a) Naive Bayes (NB): is a supervised machine learning method that utilizes Bayes theory to identify consumer attitudes [41, 42].

b) Support Vector Machine (SVM): is a supervised machine learning algorithm that has been used for understanding consumer interests [43,44].

c) Logistics Regression (LR): is another machine learning model that has been used to analyze user interests from Twitter data [45, 46].

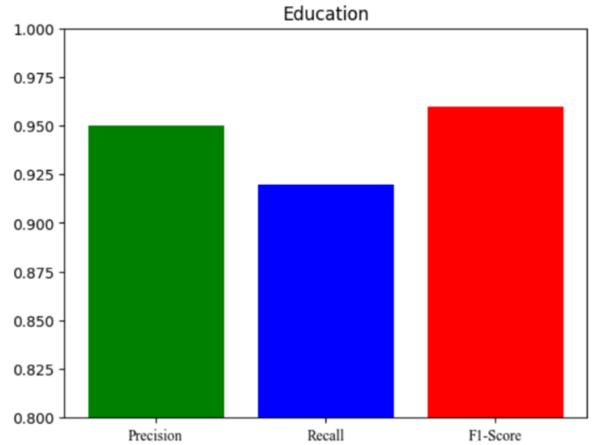
d) Long- Term Short Memory (LSTM): A deep learning model that can be used to perform sentiment analysis on social.

Media [36,47,48].

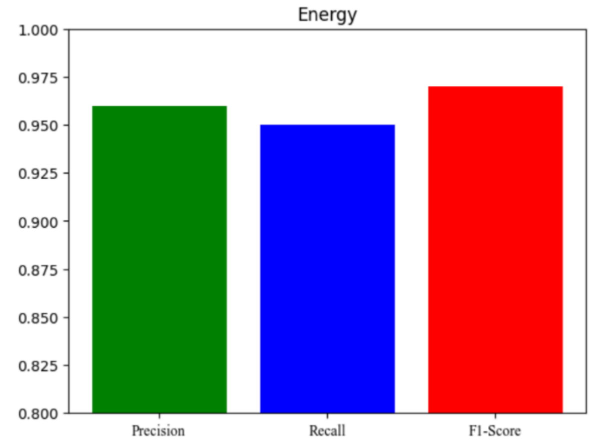
D. Result and Discussion

The empirical experimentation is performed for the IoT services consumers' interests classification model against the five groups of the IoT services' consumers' interests where the precision, recall, and F1-Score is calculated for each category as shown in Fig. 4. The highest result in precision appeared in the health category to reach 0.96 as shown in Fig. 4(c). Fig. 4(c) shows the highest recall score of 0.95. The highest result in F1-score appeared in the education category and energy category and it is recorded at 0.95 and 0.96 respectively.

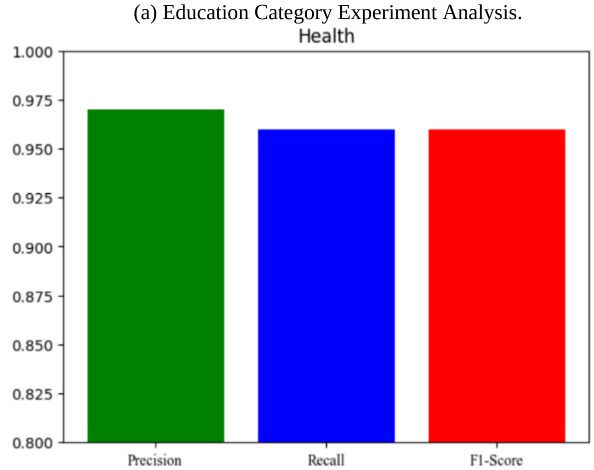
This study used several methods for conducting a comparative study. The LSTM model is compared with three well-known models: NB, SVM, and LR. These models are evaluated in terms of accuracy. Fig. 5 shows the accuracy results for our model compared with other classifiers. Compared to LSTM, SVM, and LR, Naive Bayes performed the worst with an accuracy score of 0.82. Conversely, LSTM has the highest accuracy score when compared to other methods. The LSTM achieved an accuracy of 0.96. Fig. 6 illustrates the training accuracy and validation accuracy of the proposed model. According to the results, the proposed model can identify consumers' interests from social media effectively, resulting in high accuracy in IoT devices and services recommendations. Fig. 7 illustrates the IoT services consumers' interests classification model confusion matrix. The LSTM model correctly predicted 0.96 tweets, while it mis-predicted 0.4.



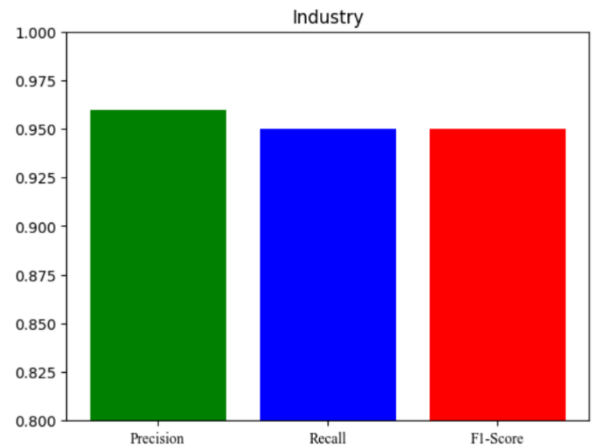
(a) Education Category Experiment Analysis.



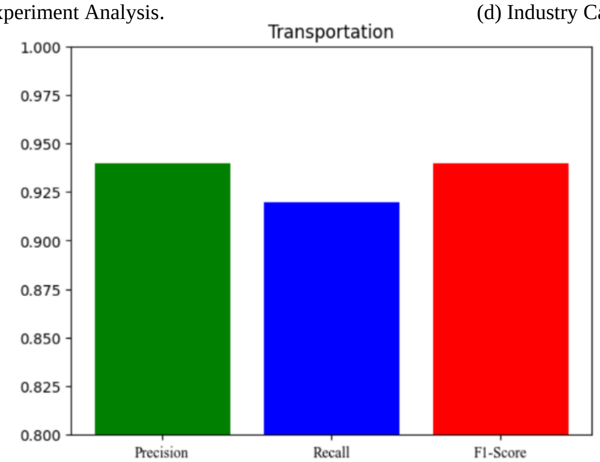
(b) Energy Category Experiment Analysis.



(c) Health Category Experiment Analysis.



(d) Industry Category Experiment Analysis.



(e) Transportation Category Experiment Analysis.

Fig. 4. The IoT Services Consumers' Classification Model Empirical Experimentation Analysis.

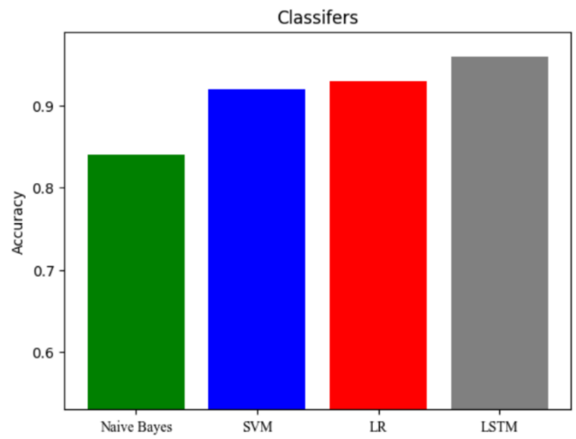


Fig. 5. Accuracy of the Proposed Model Compared to other Classifiers.

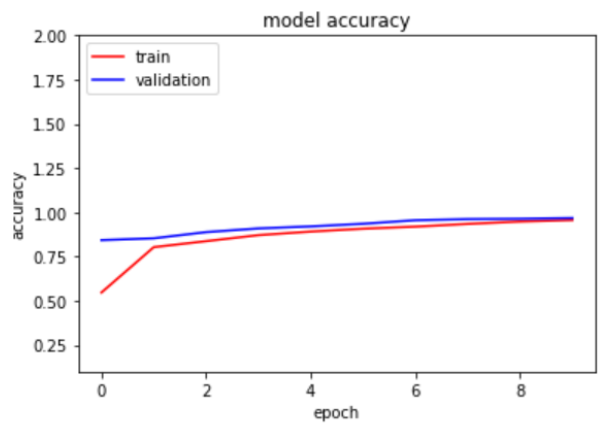


Fig. 6. The Accuracy of the Proposed Model.

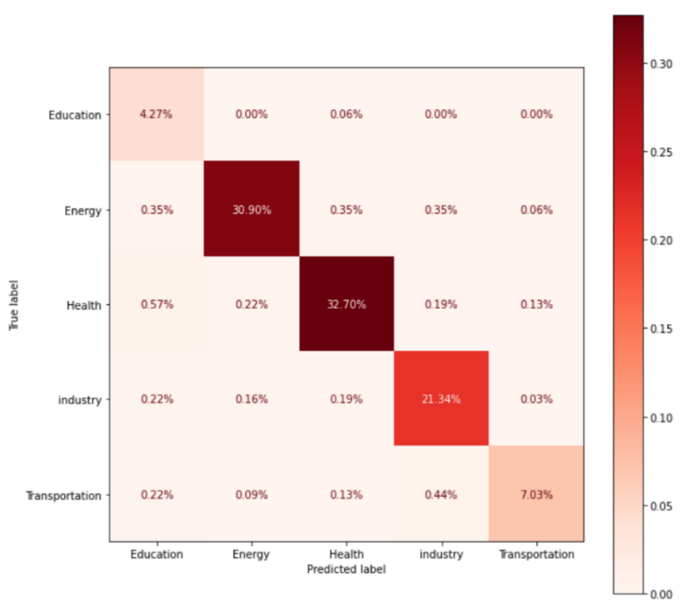


Fig. 7. The IoT Services Consumers' Classification Model Confusion Matrix.

V. Conclusion

IoT devices connected to the internet have increased dramatically and played an important role in several domains such as health, energy, education, transportation, industry, and other domains. With this increase, IoT services' consumers find it difficult to choose the suitable IoT devices and services that solve their problems. This paper explores how consumers' knowledge about IoT services can be used to predict suitable devices and services. Therefore, a knowledge-based IoT recommendation system is introduced based on SOA to allow IoT device and service providers to register and advertise their IoT device and services and recommend IoT devices for IoT services consumers based on their interest. In particular, this paper presents an IoT services consumers' interests classification model that uses a deep learning model namely, Long Short-term Memory (LSTM), to classify IoT services' consumers based on their interest. In order to demonstrate the feasibility of our proposed approach, a real-world IoT dataset is collected from Twitter that includes more than 15,791 tweets, a prototype system is implemented, and empirical experiments were conducted. The results of the experiments on the IoT services consumers' interests classification model were promising where the overall average results in accuracy, precision, recall, and F1-score are 0.96, 0.95, 0.96, and 0.95 respectively.

In future work, the IoT recommendation system will be extended to be a hybrid recommendation system, which can be enhanced by collaborative filtering techniques. Furthermore, several IoT categories and languages such as Arabic will also be added to evaluate the accuracy of the proposed model. As part of our recommendation system, videos can also be added to explain how to use IoT devices.

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