IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received September 6, 2019, accepted September 24, 2019, date of publication October 8, 2019, date of current version October 22, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2946204

Automating E-Government Services With Artificial Intelligence

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ABSTRACT Artificial Intelligence (AI) has recently advanced the state-of-art results in an ever-growing number of domains. However, it still faces several challenges that hinder its deployment in the e-government applications–both for improving the e-government systems and the e-government-citizens interactions. In this paper, we address the challenges of e-government systems and propose a framework that utilizes AI technologies to automate and facilitate e-government services. Specifically, we first outline a framework for the management of e-government information resources. Second, we develop a set of deep learning models that aim to automate several e-government services. Third, we propose a smart e-government platform architecture that supports the development and implementation of AI applications of e-government. Our overarching goal is to utilize trustworthy AI techniques in advancing the current state of e-government services in order to minimize processing times, reduce costs, and improve citizens' satisfaction.

INDEX TERMS Artificial intelligence, deep learning, E-government, web services.

I. INTRODUCTION

Artificial Intelligence (AI) has been around for some decades in several theoretical forms and complicated systems; however, only recent advances in computational powers and big data have enabled AI to achieve outstanding results in an ever-growing number of domains. For example, AI have tremendously advanced the areas of computer vision [1], medical applications [2], natural language processing [3], reinforcement learning [4], and several other domains.

AI can be defined as the ability of a computer to imitate the intelligence of human behavior while improving its own performance. AI is not only robotics, rather an intelligent behavior of an autonomous machine that describes the brain of the machine and not its body; it can drive a car, play a game, and perform diverse sophisticated jobs. AI is a field that falls at the intersections of several other domains, including Machine Learning [5], Deep Learning [6], Natural Languages Processing [3], Context Awareness [7], and Data Security and Privacy [8]. Figure 1 illustrates the intersections and relationship of the AI field with related fields.

Machine Learning (ML) is the ability of an algorithm to learn from prior data in order to produce a smart behavior and make correct decisions in various situations that it has never faced before. ML algorithms are enabled by training a computational model, which is the process of exposing an algorithm to a large dataset (e.g., citizens' demographics) in order to predict future behaviors (e.g., employment rates). The process of learning from prior datasets is known as a supervised learning.

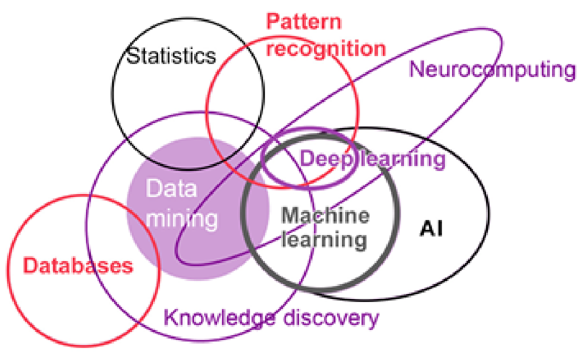

FIGURE 1. AI intersections and relationship with other fields.

Unlike traditional ML algorithms, Deep Learning, a subfield of ML, has emerged to outcome the limitations of prior ML algorithms. Deep learning can be defined as a mapping function that maps raw input data (e.g., a medical image) to the desired output (e.g., diagnosis) by minimizing a loss function using some optimization approach, such as stochastic gradient descent (SGD) [9]. Deep learning algorithms,

The associate editor coordinating the review of this manuscript and approving it for publication was Aniello Castiglione.

inspired by the neural networks in the human brain, are built with a large number of hierarchical artificial neural networks that map the raw input data (inserted at the input layer) to the desired output (produced at the output layer) through a large number of layers (known as hidden layers), and thus the name deep learning. The hidden layers are responsible for the actual mapping process, which is a series of simple but nonlinear mathematical operations (i.e., a dot product followed by a nonlinear process). The main advantage of deep learning is that it does not require feature engineering.

Despite the fact that deep learning has improved the state-of-art results in several domains, it is still evident that e-government applications face several challenges regarding adapting deep learning [10]. First, given the recent and rapid advances in the deep learning domain, it is becoming more difficult to find experts of this technology who are capable of developing efficient and reliable AI applications, especially in third world countries. Second, the development lifecycle of AI projects, specially deep learning, has introduced a new set of development challenges. In particular, traditional software development focuses on meeting a set of required functional and non-functional requirements; in contract, deep learning development focuses on optimizing a specific metric based on a large set of parameters, which is done in a unsystematic search approach. Third, integrating AI and deep learning applications in e-government services requires strong policies and measures on data security and privacy. However, there are still challenges that hinder the creation of concrete standards for data security and privacy, including citizen-government trust, transparency, and other technical difficulties related to developing and implementing secure systems.

E-government is the application of employing advanced electronic techniques–and web services–to present, exchange, and advance the government's services for citizens and businesses with a goal of improving the productivity while reducing the cost. E-government plays a critical role in advancing the economy of the government, citizens, and industry, especially for developing countries. It facilitates the business-to-business transactions and tasks (B2B), brings customers closer to businesses (B2C), allow productive interactions between the government and citizens (G2C), government and enterprises (G2B), and inter-agency and relationships (G2G) in more convenient, transparent and economic ways [11]–[14].

The ultimate goal of the e-government is to enhance the quality and efficiency of the government services while reducing cost. Moreover, implementing e-government applications can foster several other advantages including, but not limited to, the following:

- Transparency: e-government applications and media outlets can enhance the government transparency on its policies and ongoing projects providing easier access to up-to-date news and notifications.
- Trust: providing access to services and government information via transparent and easy-to-use technologies can critically enhance the trust between citizens and government.
- Citizen participation: e-government applications can ease the process of involving citizens in decision-making and conducting surveys, which can reflect the citizens' opinions and improve their participation in building their future.
- Environment support: e-government services eliminate large amounts of paper applications and energy requirements for running and operating facilities and processing units leading to supporting the environment.

In contrast, implementing e-government applications still faces several challenges, including the following:

- Trust: trusting online services depends heavily on a couple of factors including, the citizens trust in the government itself, the quality of the online services, and the personal believes (e.g., there still a large number of citizens who prefer to handle paper applications rather than web services).
- Lack of experts: implementing high-quality online services requires the establishment of the right team of experts that covers all involved practice areas from web development to security and privacy.
- Inaccessibility: several third world countries still face significant issues on accessing the internet and its services.
- Security: state-of-the-art security measures are required to secure e-government applications and the citizen's privacy.

Recently, many countries have adopted e-government services in various departments and many autonomous applications [15]. While there are several studies conducted for enhancing e-government services, only a few of them address utilizing recent advances in AI and deep learning in the automation of e-government services [16]–[19]. Therefore, there is still an urgent need to utilize state-of-the-art AI techniques and algorithms to address e-government challenges and needs.

In this paper, we propose a novel framework that utilizes recent advances in AI to improve the e-government systems and their interactions with the citizens. First, we propose a framework to automate and facilitate the management of e-government systems using AI techniques. Second, we develop and present several deep learning models that aim at automating e-government services for Arabic speaking countries including automatic recognition of hand-written digits and letters and sentiment analysis. Third, we propose an platform for smart e-government services development and implementation.

The rest of this paper is organized as follows: Section two presents the current state of the national and international e-government performance indices. Section three proposes an advanced management framework for e-government information resources. Section four presents our deep learning models. Section five suggests a platform for smart e-government services. The conclusion comes in the sixth Section.

II. E-GOVERNMENT PERFORMANCE

Before introducing our proposed approach, we discuss the current state of the e-government industry in several countries around the world.

According to United Nation E-Government Survey of 2018 [20], the European Union is leading in implementing e-government applications, followed by the USA, Asia, and then Africa. This reflects the lack of infrastructure at a low level of the E-Government Development Index (EGDI) countries. Table 1 displays the countries' EGDI and online services index according to the region. Europe is the leader in the development index, technical infrastructure, and online services, while Africa is located at the bottom of the table due to its poor infrastructure, communication systems, and carrier services (especially internet providing services).

TABLE 1. A comparison of E-government developing index and online service index by region.

Continent	E-government Developing Index	Online Services Index
Europe	0.77	0.79
America	0.59	0.61
Asia	0.57	0.62
Africa	0.34	0.36

TABLE 2. EGDI rank of the gulf countries in 2016 and 2018.

Country	2016 Rank	2018 Rank
United Arab Emirates	29	21
Bahrain	24	26
Saudi Arabia	44	52
Oman	66	63
Qatar	48	51

Table 2 illustrates the EGDI worldwide ranking for the Gulf Countries–the case study of our paper (i.e., United Arab Emirates, Bahrain, Saudi Arabia, Oman, Qatar, and Kuwait) in 2016 and 2018 respectively. It is evident from the table that e-government services can vary from one year to another depending on several factors, including the fact that some online services can have opposite effect on transparency and user privacy.

Investing in both human resources and technical infrastructure are key roles for advancing the development, implementation, and efficiency of e-government systems and services. Most countries started to realize the importance of e-government impacts; and therefore, these countries started to invest more resources–both human and financial–in enhancing the e-government applications. Such countries moved from low-EGDI to medium-EGDI. Other countries moved from high-EGDI to very-high-EGDI. Figure 2 illustrates some of the services that e-government provides

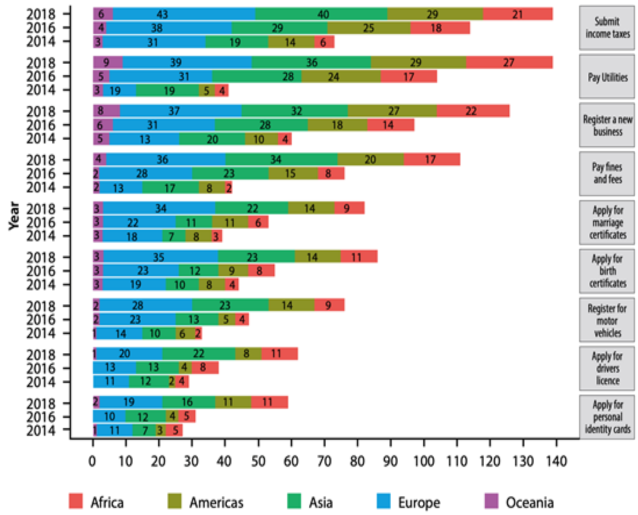

FIGURE 2. E-government services improvement between 2014 to 2018 by region [20].

based on geographical region, showing the improvement of e-government services between the years 2014 and 2018 [10].

According to the "Arab Digital Technologies for Development Report (2019)" [21], Gulf Countries have been paying special attention to integrating AI in their e-government services and infrastructures. In addition, they aim to employ AI to assist policymakers to measure the level of digitization and sophistication in delivering e-government services to citizens. Gulf Countries are leading many advanced projects for developing and applying e-government infrastructures, platforms, and services. Neom [22]–a mega, high-tech, AI city being built in Saudi Arabia–is a good example of the AI-infused projects and advancements towards cutting-edge e-government systems and infrastructures.

It's important to mention here that the underlying background and cultural believes of the citizens of these countries may also play a critical role in accepting the automated e-government services, especially services that may require transmitting sensitive information and include face recognition techniques. Recently, Saudi Arabia has announced the formulation of an AI government agency. The UAE had also established an AI agency in 2016.

III. MANAGEMENT OF GOVERNMENT INFORMATION RESOURCES

Huge amounts of data (i.e., Big Data [23]) is being generated every second from myriad of sources, including a plethora of homogeneous–structured and unstructured–data related to e-government and its services. Despite this rapid growth in data generation and consumption, there is still a missing piece in the big picture of Big Data–the management of government information resources. Proper and automated systems that address the management of government information has become an interest to academic institutions, research communities, and especially government agencies [24]. Moreover, the management of information resources plays a critical role in the overall pipeline of e-government services from collecting end-user data, to storage, and processing. In this section, we propose an architecture for centralized management of e-government information resources that mainly focuses on the utilization of AI, Big Data, and Internet of Things.

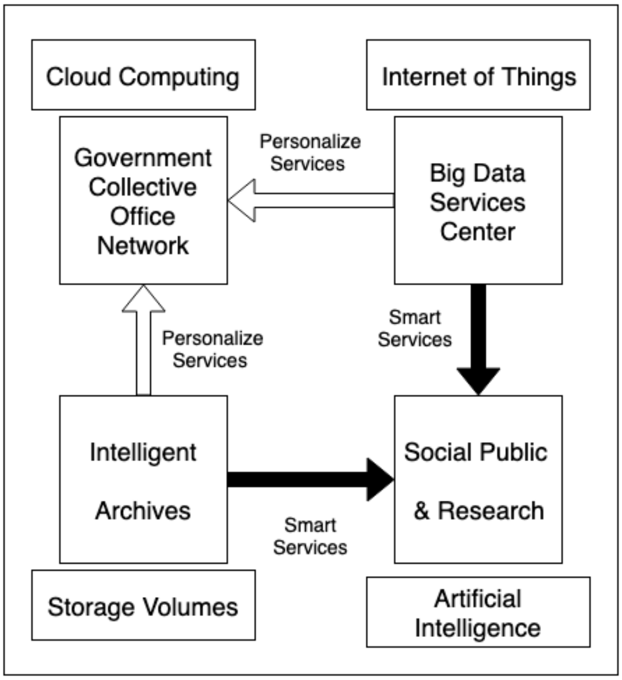

FIGURE 3. An architecture overview for a centralized e-government information management framework.

Figure 3 illustrates our proposed framework for a centralized management of e-government information resources. It consists of four main components: Government Collective Office Network, Big Data Services Center, Social Public and Research, and Intelligent Archives. These components utilize the advances in cutting-edge technology to enhance and facilitate the production, processing, and presentation of e-government resources, including, Cloud Computing services, Internet of Things, AI, and Storage utilities. We address in this paper AI technology being one of the active areas at the moment in addition to the challenges we mentioned in the Introduction Section. We also present several applications (i.e., deep learning models) that depict how AI applications can help automating several e-government services (we present our models in the next Section).

The Government Collective Office Network is responsible to implement and ensure the correctness of e-government polices and services in alignment with all government offices and agencies. Big Data Services Center is responsible for all processes and policies regarding Big Data (collecting, storing, processing, transmitting). Moreover, this unit plays a critical role in ensuring the privacy and security of the citizens and government data. Social Public and Research is the unit responsible for providing e-services for the citizens and research organizations. It also includes a research agency concerned with advancing the current state of e-government ecosystem. Intelligent Archive unit is responsible to digitize paper documents and applications and provide smart and personalized services to other units that require accessing and consuming digital data.

IV. AUTOMATING E-GOVERNMENT SERVICES WITH DEEP LEARNING

Despite the existence of a plethora of e-government resources and data that could be utilized in ever-growing number of applications, data is not being utilized in a manner that facilitates and advances the current e-government services using data-driven approaches. Utilizing advanced deep learning algorithms can significantly improve the current state of e-government services and systems to become more efficient and economic.

In this section, we introduce several deep learning models that aim at automating several e-government services. We trained the models to high-accuracy results in the Arabic language to support e-government systems in Arabic-speaking countries. In particular, we developed deep learning models for (1) hand-written letters recognition, (2) hand-written digits recognition, and (3) Arabic sentiment classification. Each one of our trained models can be utilized in several services to automate the current systems. However, before presenting the models, we first provide the reader with a brief background on deep learning and how it works.

A. DEEP LEARNING

Deep learning is a subfield of machine learning that has achieved outstanding results across several domains, such as computer vision and natural language processing. Deep learning can be defined as a mapping function between raw input data and the required output. It is inspired by the brain's neural networks and thus its algorithms use artificial neural networks (also known as deep learning models) to optimize a loss function, often, using an iterative approach such as stochastic gradient descent (SGD).

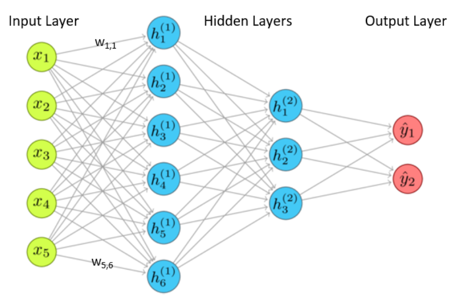

FIGURE 4. Deep learning architecture overview.

Neural networks are organized in particular layers divided into three categories: an input layer, hidden layers, and an output layer. Figure 4 depicts a general architecture for deep neural networks. The input layer (in Green) is responsible for entering the data to the neural network. The hidden layers (in Blue) are responsible for transforming the data by applying a simple but nonlinear mathematical transformation. The transformation is calculated by multiplying each input value by a corresponding weigh and then adding up these results to produce the activation value after applying an activation function to the weighted product (activation functions are used to break the linearity of the transformation).

Equation 1 is a generalization of this transformation, where $\hat{y}$ represents the network's output (i.e., prediction results), x_i represents the input features, w_i represents the weights of the synapses connecting the neurons, b represents the bias value, and the function represents an activation function.

$$\hat{y} = f(\sum_{i=1}^{n} x_i w_i + b) \tag{1}$$

ReLU (Linear Rectified Unit) is one of the widely used activation functions in the hidden layers. It converts all negative values to zeros; i.e., $ReLU(x) = max0, x$. The output layer (in Red) produces the output of the neural network. There is only one output layer, but it may include one or more neurons, each responsible to output a specific value. For example, in the case of classifying hand-written digits, the output layer has ten neurons, each responsible to trigger when a specific digit image is input to the neural network. Output layers also use activation functions, such as the *Softmax* function (also known as *SoftArgMax*) which accepts a vector of values and outputs their probability distribution. Equation 2 illustrates *Softmax*, where each element x_i is normalized by dividing it by the sum of all elements of the vector x.

$$softmax(x)_i = \frac{exp(x_i)}{\sum_j exp(x_j))} \tag{2}$$

The network architecture of a deep learning model refers the overall organization of its layers. These layers can be organized in different structures with different number of neurons in each layer and a distinct set of parameters (e.g., activation function and bias). Building an efficient neural network is thus a search problem focused on finding a proper architecture and configuration that will optimize a specific loss function. Loss functions are used to assess the network s performance by comparing its prediction results to the actual results in the supervised learning approach. A good explanatory example for a loss function is the Mean Squared Error (*MSE*) illustrated in Equation 3, where y_i represents the actual output, and y_i represents the predicted output.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2. \tag{3}$$

B. HAND-WRITTEN LETTERS RECOGNITION

Automating the process of converting hand-written text to digital text can play significant roles in automating e-government systems [25]. For example, hand-written text recognition can advance the postal service filtering systems that currently depend on human employees to read the address on each envelope and forward it to the correct destination. It can also be used to archive and digitize files and written applications. To facilitate automating this service, we built a deep learning model that can recognize Arabic hand-written letters and convert them to digital text.

To build this model, we used the Arabic Hand-Written Characters dataset [26], which includes 16,800 (32x32 pixel) images of Arabic characters from "Alef" to "Yeh". 14,000 images were used for training while the remaining 2,800 images were used for testing. We retrained the ResNet18 model [1] for this classification problem using the transfer learning technique. The architecture of Renet18 is shown in Figure 5. We used the Cross Entropy Loss function to evaluate the performance of the model. Our model achieved a test accuracy score of 98.41%. Figure 6 illustrates a sample of the dataset. Figure 7 illustrates the accuracy versus each training cycle–epoch).

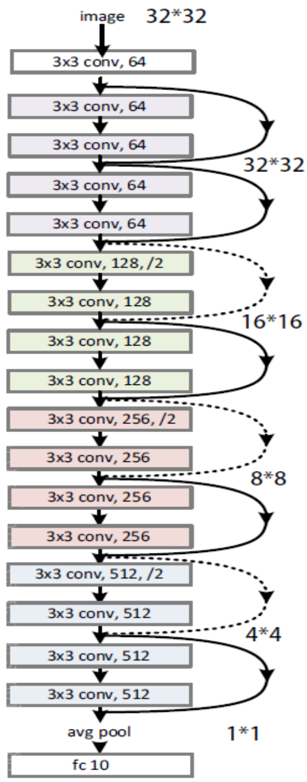

FIGURE 5. ResNet18 architecture overview [1].

C. HAND-WRITTEN DIGITS RECOGNITION

Similar to automatic hand-written letters recognition, hand-written digits recognition can play significant roles in automating e-government services. For example, it can be used to facilitate detecting digits from paper applications, cars license plates, home addresses, street numbers, and other products. It can also be used to archive and digitize files and written applications.

Given the fact that the problem on hand (digits recognition) is similar in nature to letters recognition, we applied the

FIGURE 6. A sample of the Arabic hand-written letters dataset.

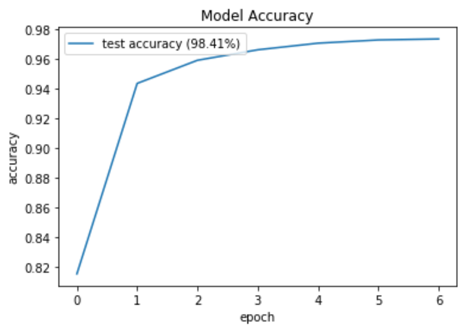

FIGURE 7. The accuracy over training cycles (epochs) of our trained model.

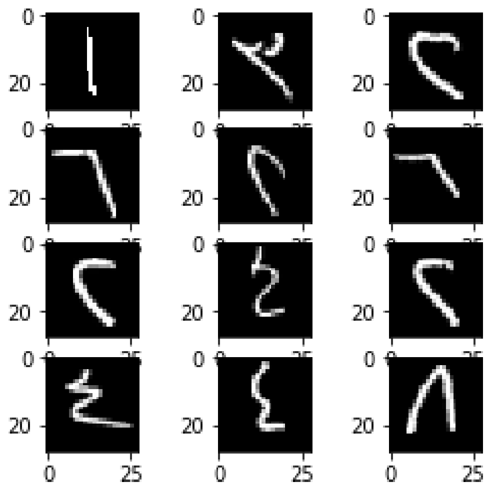

FIGURE 8. A sample of the hand-written digits dataset.

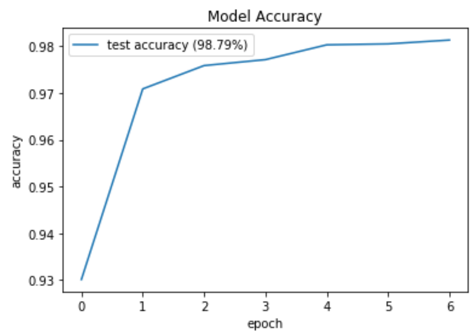

FIGURE 9. The accuracy over training cycles of our trained model.

same steps here to develop the deep learning digits classifier (i.e., we used the ResNet18 architecture). To train this architecture, we used the Hand-Written Digits dataset [27], which includes 70,000 images of the digits 0-9 (each image size is 28x28 pixels). We used 60,000 images for training and 10,000 images for testing. Figure 8 illustrates a sample of the dataset. Our model achieved a test accuracy score of 98.79%. Figure 9 depicts the test accuracy of our model.

It's important to clarify here that while the Arabic digits are the ones written with this shape 0,1,2,...,9, Arabic governments often use the Indian digits (the ones shown in Figure 8) for historical reasons.

D. ARABIC SENTIMENT ANALYSIS

One of the most common application of deep learning is to identify and classify opinions of users in order to quantify and study their attitude towards a particular topic, service or a product (this analysis is known as sentiment analysis) [28]. We greatly believe that sentiment analysis can help advance the e-government services in several aspects. For example, automated sentiment analysis can be integrated in e-government services to analyze the overall efficiency of these services leading to improving the service quality and addressing citizens' needs.

In order to help automating sentiment analysis services, we present a deep neural network that is capable of classifying Arabic written text to negative (given class 0) or positive (given class 1). For this classification task, we built a unique architecture based on recurrent neural networks. The architecture of our model is illustrated in Figure 10.

To train our neural network, we used the Arabic Products Review Dataset [29], which includes 1,648 reviews annotated with their sentiment (i.e., positive or negative). A sample of the dataset is illustrated in Figure 11. We used 1,318 reviews to train the model and 330 reviews to test the performance of the model. Our trained model achieved a test accuracy of 95.98% (see Figure 12).

E. AUTOMATED ARCHIVE INDEXING

There is an urgent need to transfer and digitize the huge amounts of written data and applications in order to be utilized in AI. During this transferring procedure, we should evaluate the importance of the data to be transferred based on the archive's management. We need to classify, tag, and index this data in a way that we keep it easy and useful to use for AI techniques. It is worth to mention that this technique varies from the traditional database archiving. Traditionally, such data used to be stored in a separate driver in a specific data structure. Our approach focuses on classifying, indexing, and recognizing government information resources. These resources will be filed and packaged based on the output

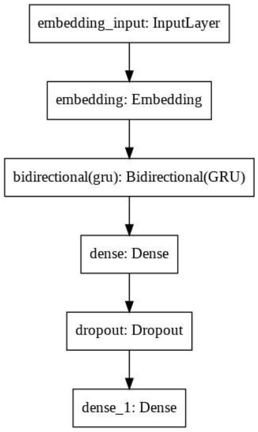

FIGURE 10. **The architecture of our sentiment analysis classification model.**

Class (0: negative, 1:positive)	Statement
0	غير جيدة وخفيفة جداً لاأنصح بها
1	ممتاز جداً
1	لابتوب مناسب وحلو للاسبتخدام الشخصي
1	جميل جداً والأجمل شكله وكتابته
0	هذا السلفي ستيك مافي ازرار
1	اللعبة رائعة ورسومها خرافية

FIGURE 11. **A sample of the Arabic products reviews dataset with their classes.**

of the transferring methods that will be stored in a different data structure with means of future preservation. Therefore, the overall goal is how to link and qualify the political materials by using different methods of AI such as sentiment analysis, entity extraction, tokenization, and parts of speech tagging.

Another goal for the archiving government resources is providing public and private information services. Such services can be learned and used from well-trained Machine Learning models that are able to provide reliable decision making and consultation systems, such as automated questions answering system. In order to create such services, there should be knowledge management techniques used for user behavior analysis in order to apply machine learning algorithms, which we proposed in the previous section, and further propose an implementation framework in the next Section.

V. SMART E-GOVERNMENT PLATFORM

The synergies of four basic technologies, including semantic web, multi-agent systems, autonomic computing, and AI techniques, can lead to developing an advanced platform that supports smart web for better e-government transactions and services. In this section, we propose an architecture for a smart e-government platform that assist and guides towards efficient implementation of AI-integrated e-government services. Figure 13 depicts our proposed platform architecture, which consists of two main layers: a basic traditional layer

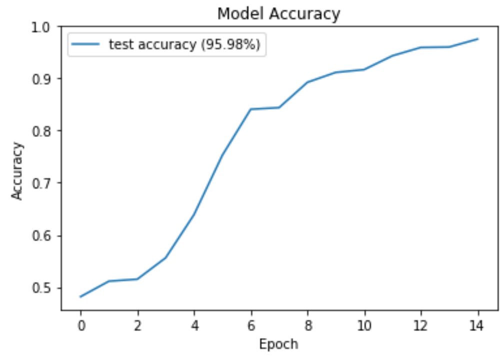

FIGURE 12. **The accuracy over epochs of our trained model for classifying Arabic products reviews.**

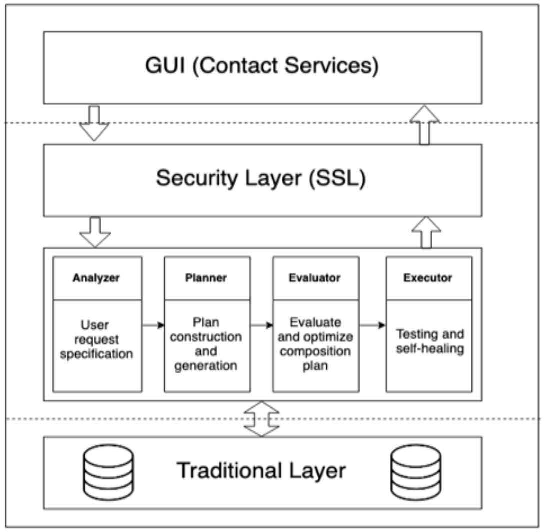

FIGURE 13. **Architecture overview for a smart e-government services platform.**

and and a autonomous smart layer. The traditional layer acts as a link between e-government legacy systems and the proposed platform. The autonomous smart layer consists of three layers: a smart GUI Citizen's Service Layer, Security Layer, and a Functional Layer. We explain each of the layers as follows.

A. SMART CONTACT CITIZEN'S SERVICES LAYER

This layer acts as an interface between the citizen and the e-government services backend. It is responsible to present the appropriate services using autonomous intelligent agents that coordinate and manage the existing services while introducing new personal services that meets the citizens' needs.

B. SECURITY LAYER

This layer is responsible to implement strict policies and security measures to guarantee the security and privacy of the e-government services and data sharing applications. This layers must be able to identify different type of threats and take the appropriate actions automatically. AI techniques can be utilized to identify attacks, threats, and potential risks,

FIGURE 14. Open e-government workflow.

then notify decision makers, and propose efficient defense mechanisms.

C. FUNCTIONAL LAYER

This layer plays an important role in our proposed system. Its main goal is to provide and extend e-government automatic services and the core functionality for the above mentioned layers. The composition plan of this layer consists of four phases:

- Analysis: this phase stars from the abstract specification to a citizen request and it aims to determine the required service in a meaningful way.
- Planning: where the discovery and configuration of the plan are created, and this process is done by the help of intelligent agents and AI techniques.
- Evaluation and optimization: which is responsible to find the best plan in terms of user specifications.
- Execution: since some problems of inconsistency may occur at run time, so reassessment and re-planning are necessary to ensure the proper execution of the services.

This will help to create open e-government that will produce a huge amount of organized data and information that help the public sector to play a vital role in supplementing citizen services. In the recent years, governments have established different sets of frameworks and regulations that enabled open citizen services, new e-government markets, created smart products, and enhanced citizen-government transparency and trust.

Different government agencies must provide detailed reports with keeping in mind the differences between central oversight and initiatives. Other agencies are appointed based on their governmental background, policies, and connection. Such agencies' leaders often do not serve long enough to witness the change since they tend to focus more on reforming policies rather than reforming the process. This approach has been implemented and articulated around the world by different governments to facilitate the governing approach which will increase the public trust and establish a more reliable and transparent system that promotes democracy and provides the more efficient government (see Figure 13).

VI. CONCLUSION

With the recent advances in AI and deep learning technologies, more government agencies are starting to use such technologies to improve their systems and services. However, a large set of challenges hinder the adoption of such technologies, including the lack of experts, computational resources, trust, and AI interpretability.

In this paper, we introduced the definitions of artificial intelligence and e-government, briefly discussed the current state of e-government indices around the world, and then proposed our solutions to advance the current state of e-government, considering the Gulf Countries as a case study. We proposed a framework for management of government information resources that help manage the e-government lifecycle end-to-end. Then, we proposed a set of deep learning techniques that can help facilitate and automate several e-government services. After that, we proposed a smart platform for AI development and implementation in e-government.

The overarching goal of this paper is to introduce new frameworks and platform to integrate recent advances in AI techniques in the e-government systems and services to improve the overall trust, transparency, and efficiency of e-government.

ACKNOWLEDGMENT

The authors would like to thank the anonymous authors for their time and effort reviewing this paper.

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