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# An Augmented Reality Question Answering System Based on Ensemble Neural Networks

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**ABSTRACT** This paper proposes a classification algorithm based on ensemble neural networks. In the training phase, the proposed algorithm uses a random number of training data to develop multiple random artificial neural network (ANN) models until those ANN models converge. Those models with lower accuracy than the threshold are filtered out. The remaining highly accurate models will be used to predict the output in the testing phase. Meanwhile, the accuracy of ANN models is presented as a weighting value in the testing phase. In the testing phase, the testing data are loaded into the selected ANN models to predict the output class. The output values are multiplied by the corresponding weighting values of ANN models. Then the weighted average of the outputs can be obtained. Finally, the predicted output is converted into the predicted class. We design an augmented reality question answering system (AR-QAS) applying and implementing the proposed algorithm on mobile devices. AR-QAS offers an interactive user interface and automatically replies according to user's queries. By comparing with the logistic regression method and the ANN method, the experiment results demonstrate that the proposed algorithm offers the highest accuracy.

**INDEX TERMS** Data mining, artificial neural network, ensemble neural networks.

## I. INTRODUCTION

In recent years, data mining has drawn much attention. This technology provides an effective way of extracting useful information or knowledge out of a big data set. The information and knowledge can be used in many areas, such as marketing analysis, fraud detection, customer retention and so on [1].

Classification and prediction processes of data mining can be used to indicate important data classes or predict future data trends. Therefore, artificial neural network (ANN), which can process non-linear and complex data even when the data are noisy or the data relationship is unknown, is a powerful data mining classifier [2]. However, the ANN might produce an incorrect training model with overfitting problems. Subsequently, this model will lead to an incorrect prediction. In order to improve the accuracy of the existing ANN algorithm, a classification algorithm based on ensemble neural networks (ENNs), which uses a random number of training data to develop multiple random artificial neural network models for the promotion of existing ANN, is proposed in this study.

The proposed algorithm includes two phases: the training phase and the testing phase. In the training phase, multiple random ANN models and the corresponding training data are generated at first. Those training data are used to train ANN models until those ANN models converge. However, if a random number of training data include incur overfitting, the accuracy of trained ANN models will decline. Thus, those models with lower accuracy than the threshold will be filtered out, and the remaining highly accurate ANN models will be used to predict the output in testing phase. Meanwhile, the accuracy of ANN models is presented as a weighting value in the testing phase. In the testing phase, the testing data are loaded into the remaining ANN models to predict the output class. The output values are multiplied by the corresponding weighting values of artificial neural network models. Then the weighted average of the outputs can be obtained. Finally, the predicted output is converted into the predicted class. This study designs an augmented reality question answering system (AR-QAS) which can apply and implement the proposed algorithm on mobile devices.

AR-QAS offers an interactive user interface and automatically replies according to user's queries [3]. With the AR technology, users can take picture of guiding flyers by their mobile phones. While the image is recognized, 3D character will be produced by AR technology. The QAS includes four steps in order to process and classify the input requirement from users and responds with the appropriate classes of the input queries which are accurate answers to the users. In this study, logistic regression, existing ANN algorithm and the proposed algorithm will be implemented in QAS and compared to derive the best classification method according to accuracy.

The remaining of the paper is organized as follows. The literature reviews of machine learning algorithms for QAS are discussed in Section 2. The proposed AR-QAS and the classficiation algorithm based on ENNs are clearly illustrated in Section 3. A case study of the proposed classification algorithm along with the system evaluation and discussion of the experiment results are given in Section 4. In Section 5, the final conclusion, suggestion and future work are provided.

## II. LITERATURE REVIEWS

Several studies modelized the QAS as information retrieval and classification issues. The process of a QAS includes: (1) retrieving the words by segmenting a query sentence, (2) generating a vector space model (VSM) based on the term frequency and inverse document frequency (TF-IDF), and (3) performing a classification algorithm to determine a suitable problem class based on the analysis of the VSM of query sentence. Therefore, the the advantages and limitations of classification algorithms (e.g., logistic regression, ANN, and ENNs) are discussed in the following subsections.

### A. LOGISTIC REGRESSION

In statistics, logistic regression is a type of probabilistic statistical classification model [4]. It is also used to predict a binary or dichotomous outcome variable [5]. The logistic regression can be used to explore the relation between the response variable and a number of explanatory variables. The outcome variable has only two possible Classes which are 1 and 0 with the [6, Eq. (1)].

$$E(Y = 1|x) = \pi(x), \tag{1}$$

where $Y$ denotes the outcome variable, $x$ denotes a value of the independent variable and $E$ is the expected value of $Y$, given the value $x$ [5].

The logistic regression model can be written as Equation (2).

$$0 \leq \pi\ (x) = \frac{e^{\beta_0+\beta_1 x_1+\cdots+\beta_k x_k}}{1 + e^{\beta_0+\beta_1 x_1+\cdots+\beta_k x_k}} \leq 1, \tag{2}$$

where $\pi\ (x)$ is the logistic transformation, and $\beta_k$ is parameter of logistic regression model [6].

This model defines a curvilinear relation between the mean of the response variable and the explanatory variables, which is equivalent to Equation (3).

$$g(x) = \frac{\pi\ (x)}{1 - \pi\ (x)} = e^{\beta_0+\beta_1 x_1+\cdots+\beta_k x_k}, \tag{3}$$

where $g(x)$ is linear in its parameters and may infinite depending on the range of $x$ [6].

The logistic of the mean is linear in the parameters and ranges from minus to plus infinity. The slope coefficient $\beta_k$ which associated with an explanatory variable $x_i$ represents the change in $g(x)$ for an increase of one unit in $x_i$ [6].

### B. ARTIFICIAL NEURAL NETWORK

The generalization of artificial neural network) is introduced at first, including introduction and basic architecture. Next, the back-Prorogation algorithm, one of most popular ANN algorithm, establishes the weight in the multilayer and feed-forward neural network.

### C. GENERALIZATION OF ANN

ANN is non-linear mapping structures which imitate the learning process of a human brain. Also, it consists of simple computational and highly interconnected units, which are called neurons. Thus, ANNs are parallel computational models and can process complex problems [7].

ANN has been developed as generalizations of mathematical models of biological nervous systems. A first interest in neural networks emerged from McCulloch and Pitts introduced simplified neurons [8]. A neural network consists of a set of connected cells, which are called artificial neurons or nodes. The neuron receives impulses from either input cells or other neurons, perform unique function of the input and transmit the outcome to other neurons or to output cells [7].

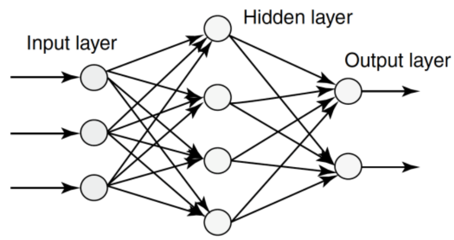


**FIGURE 1.** Multilayered neural network [8].

The basic architecture of a neural network has three layers, as shown in Figure 1. The first layers of neural network consist of input units that are known as independent variables. The second layer is a hidden layer which links each input neural and makes computation according to the provided function. The last layer is the output layer to yield the final results that are known as the dependent or response variables from hidden layer.

A typical artificial neuron and the modeling of a multilayered neural network are illustrated in Figure 2. The input signal flow $x_i$ is unidirectional. Both input signal flows and neuron's output signal $O$ flows are indicated by arrows. The neuron output signal $O$ is given by the following Equation (4) [8].

$$O = f(net) = f\left(\sum_{i=1}^{i} \omega_{,i} x_{,i}\right), \tag{4}$$

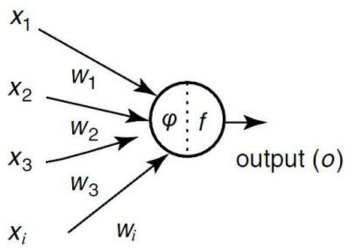


**FIGURE 2.** An artificial neuron [8].

where $w_i$ is the weight of input signal flow $x_i$ and the function $f(net)$ refers to an activation function. The variable net is defined as a scalar product of the weight and input vectors are shown in Equation (5).

$$net = \omega^{\mathrm{T}} x = \omega_1 x_1 + \omega_2 x_2 + \omega_3 x_3 + \ldots + \omega_i x_i, \quad (5)$$

where $T$ is the transpose of a matrix.

The output value $O$ is computed as [8, Eq. (6)].

$$O = f(net) = \{^{1, if\ \omega^{\mathrm{T}} x \geq \varphi;}_{0, otherwise,} \quad (6)$$

where $\varphi$ is called the threshold level.

This type of node whose output is as Equation (6) is called a linear threshold unit [8].

### *D. BACK-PROROGATION ALGORITHM*

The most popular form of neural network architecture is the multilayer perceptron with back-prorogation algorithm. The basic idea of the back-prorogation algorithm is the repeated application of the chain rule computing the influence of each weight in the network with respect to an arbitrary error function [9]. The back-prorogation algorithm can be divided into two phases: (1) forward Propagation phase; (2) weight update phase. During the forward propagation phase, each training data are inputted and propagated forward the network to compute the output. Then the output is compared with the target to calculate the delta of all output neurons and hidden neurons. Next, during the weight update phase, the delta is backward passed to each neuron and appropriately adjusts the weight of all output neurons and hidden neurons in order to minimize the error [10].

### *E. ENSEMBLE NEURAL NETWORKS*

To prevent the overfitting problems, ENNs are proposed to train ANNs and determine the classification results based on the votes from the trained ANNs. The ENNs include the following steps.

*Step 1 (Perfroms the Classical Initialization):* The number of ANNs is defined in this step for the generation of ENNs.

*Step 2 (Perfroms the Manipulation of Structure for Each ANN):* The number of layers in each ANN is defined in this step to determine the structure of each ANN in the ENNs.

*Step 3 (Perfroms the Manipulation of Layers for Each ANN):* The number of neurons in each layer of each ANN is defined in this step to generate the layers of each ANN in the ENNs.

*Step 4 (Perfroms the Manipulation of the Training Data):* The partitions of trainind data set and attributes of VSM are selected to train the weights between each two neurons for each ANN model.

*Step 5 Perfroms the Pruning Phase and the Combining Phase):* In the pruning phase, the trained ANN models with lower accuracy can be dropped out. In the combining phase, the remaining ANN models can be used to vote and estimate classification results

### *F. SUMMARY AND DISCUSSIONS*

This subsection summarizes the limitations of mentioned classification algorithms and discusses the evolutions of these algorithms for the design of QAS. Although logistic regession algorithm could analyze the linear and non-linear relationship between the eacn word and each class, the words of a query sentence were assumed as independent varables. Therefore, the larger errors might generated by the logistic regression for the query sentence with dependent words. For the analysis of dependent vectors in a VSM, the ANN algorithm was applied to estimate the relationships among words in a query sentence through hidden layers. However, the overfitting problems might exist in the trained ANN model. Therefore, the ENNs and dropout method were proposed to prevent overfitting problems, so this study proposed and implemented a classification algorithm based ENNs for QAS.

## III. THE PROPOSED AR-QAS

An AR-QAS is proposed in this section. An overview and the architecture of the AR-QAS are shown first. Secondly, the classification algorithm based on ENNs for QAS is presented in detail.

### *A. THE DESIGN AND IMPLEMENTATION OFSYSTEM*

The architecture of AR-QAS is shown in at first. Next, the complete flow of QAS is implemented and the techniques used in QAS are presented.

#### 1) OVERVIEW

The AR-QAS is implemented on the Android mobile phone, which connect the with a cloud server through the Internet. The complete architecture of AR-QAS is shown as Figure 3. The AR-QAS includes two parts: (1) mobile phones and (2) a cloud server. The mobile phone includes AR technology, voice interaction techniques and a web server client. User can use mobile device with the AR-QAS to scan particular images. While the image is recognized, 3D character (i.e., Video) will be produced by AR technology [16]. Also, if the user asks a question, the mobile device translates the question into the text form by voice interaction techniques and the text is send to QAS in cloud server to analyze the output of the answer. In the end, the output of the answer is responded to users by voice interaction techniques. The cloud server comprises the QAS, external Application Programming

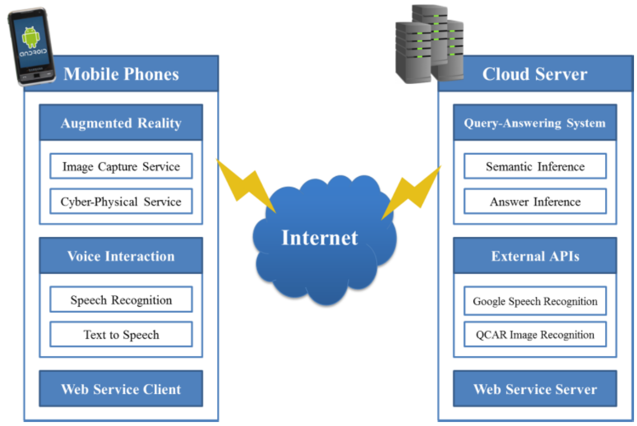


**FIGURE 3.** The complete architecture of AR-QAS [17].

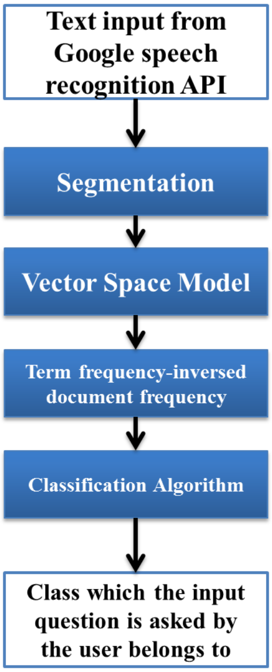


**FIGURE 4.** The flow chart of the QAS.

Interfaces (APIs), and a web service server. This cloud server provides efficient computation power for the analysis of QAS and processes the input requirement from the user [17].

#### 2) QUESTION ANSWERING SYSTEM

A question answering system is a tool that can automatically provide accurate answer according to user's question or requirement [3]. In this study, a user's question or requirement will be sent to Google speech recognition API and transformed into text form with the input of the QAS. There are four steps of the QAS: segmentation, VSM, TF-IDF, and classification. The complete flow of the question answering system including all steps and the used techniques is shown in Figure 4.

Chinese Knowledge and Information Processing (CKIP) system is a useful tool to segment Chinese sentences [18]. In this study, CKIP system segments the input sentences into terms. After segmentation, terms will be transformed into a vector by VSM according to the vector space [19]. Furthermore, the TF-IDF values of terms will be calculated and taken as the weighting factors by considering that different terms are not equally im-portant [20]. Finally, the input query will be classified into the correct class by the classification methods of data mining, such as logistic regression, existing ANN and ENNs. After the process of the QAS, the adaptive class to which the input question sked by the user belongs will be revealed. The output of the QAS will be returned to the user.

### B. THE CLASSIFICATION ALGORITHM BASED ON ENNs

The QAS is modeled as a classification process, and the classification algorithm based on ENNs is proposed. In this section, the main objective and the core problem are first introduced. Second, the definition of parameters that are used in this section is presented and briefly explained. Third, the detail and complete flow of the proposed classification algorithm based on ENNs are introduced.

#### 1) DESIGN ISSUES

ANN, which can process nonlinear and complex data even when the data are noisy or data relationship is unknown [2], is a powerful data mining classifier. However, the overfitting issue of ANN may exist to produce an incorrect training model. Subsequently, this model will lead to an incorrect prediction. Therefore, this study designs a classification algorithm that randomly trains several ANN models for the promotion of existing ANN.

The proprosed algorithm includes two phases the same as other data mining algorithms, training phase and testing phase. In the training phase, a number of ANN models are randomly generated at first. Second, a random number of training data are used to train artificial neural networks. Third, the networks with lower accuracy will be filtered out. Thus, the remaining highly accurate artificial neural network models will be used to predict the output in testing phase. Meanwhile, the accuracy of artificial neural network is presented as a weighting value in the testing phase. At last, in the testing phase, the testing data are loaded into the remaining ANN models with the high accuracy to predict the output class. Output values are multiplied by the corresponding weighting values of artificial neural network models and the weighted average of the sum of total outputs can be obtained. Finally, the predicted output is converted into the predicted class. All the parameters that will be used for the introduction of the proposed algorithm are defined and presented in Table 1.

#### 2) THE PROPOSED ALGORITHM

The proposed algorithm based on ENNs includes two main phases which are training phase and testing phase, which are shown in Figure 5 and Figure 6. The detail of two phases is presented in following subsections.

**TABLE 1.** Definition of parameters for RBPNN.

| Noation | Description |
|---|---|
| $M$ | The number of ANN models |
| $h_{max}$ | The maximum number of hidden layers |
| $c_{max}$ | The maximum number of hidden nodes |
| $r$ | The percentage of training data for testing neural networks in training phase |
| $w_{threshold}$ | The threshold level of the accuracy |
| $h_m$ | The hidden layers of the $m^{th}$ ANN |
| $c_m$ | The hidden nodes of the $m^{th}$ ANN |
| $d_{TR}$ | Total training data in training phase |
| $d_{TRTR,m}$ | Training dataset of training data in training phase |
| $d_{TETR,m}$ | Testing dataset of training data in training phase |
| $d_{TE}$ | Testing data in testing phase |
| $\omega_{m,j,g}$ | The weight associated with the link between neuron $j$ and neuron $g$ of the $m^{th}$ ANN |
| $\theta_{m,g}$ | The constant of neuron $g$ of the $m^{th}$ ANN |
| $o_{m,g}$ | The output of neuron $g$ of the $m^{th}$ ANN |
| $f(net)$ | Activation function |
| $net_{m,g}$ | The $g^{th}$ result of the network inputs $x_{m,i}$ of the $m^{th}$ ANN |
| $x_{m,i}$ | The $i^{th}$ input vector of the $m^{th}$ ANN |
| $E_{m,g}$ | The computed output error at neuron $g$ of the $m^{th}$ ANN |
| $t_{m,g}$ | The $g^{th}$ target output of the $m^{th}$ ANN |
| $\eta$ | The parameter of learning rate with $0<\eta<1$ |
| $T_{threshold}$ | The threshold level for the convergence of ANN |
| $a_{m,l}$ | The accuracy of the $l^{th}$ calculated input testing data from $m^{th}$ ANN |
| $A_m$ | The average accuracy of all $a_{m,l}$ in $m^{th}$ ANN |
| $C_k$ | The output of calculated input of testing data in testing phase form $k^{th}$ ANN |

### 3) PHASE 1: TRAINING PHASE

In the training phase, the proposed algorithm analyzes the data to discover the pattern or rule and store it in the model to recognize other unknown data.

*Step 1 (Set Parameters):* In the beginning of training phase, five parameters are selected by users, including the number of ANN $M$, the maximum number of hidden layers in each ANN model $h_{max}$, the maximum number of neurons in each hidden layer $c_{max}$, the ratio of training data to all data in training phase $r$, and the accuracy threshold of each ANN model $w_{threshold}$.

*Step 2 (Retrieve Training Data From the Database):* Each record of training data is retrieved from the database.

**TABLE 2.** The ratio of each dataset in this study.

| Parameters | The ratio of dataset to total data in the database | The definition of dataset |
|---|---|---|
| $d_{TR}$ | $a$ % | Total data in training phase (training data) |
| $d_{TRTR,m}$ | $r$% * $a$ % | Training dataset in training phase |
| $d_{TETR,m}$ | (100%- $r$%) * $a$ % | Testing dataset in training phase |
| $d_{TE}$ | 100% - $a$% | Testing dataset in testing phase (testing data) |

*Step 3. (Create Random m ANNs):* In this step, $M$ ANN models are randomly created by using selection parameters, i.e. the classical initialization for ENNs. Moreover, the number of hidden layers $h_m$ is randomly generated between 0 and $h_{\max}$ for each ANN model (i.e., the manipulation of the ANN structure for ENNs) while the number of neurons $c_m$ is randomly generated between 0 and $c_{\max}$ for each hidden layer (i.e., the manipulation of the ANN layers for ENNs).

In addition, the ratio $r$ of the training data to the total number of training data $d_{TRTR,m}$ are randomly selected (i.e., the manipulation of the training data for ENNs). The rest of training data $d_{TETR,m}$ will be used as testing data in the following training phase. Therefore, the $m^{th}$ ANN model will be trained through different training data set $d_{TRTR,m}$ and tested through different testing data $d_{TETR,m}$ in training phase. Five datasets in Table 2 are considered and grouped in this study.

*Step 4 (Train ANN Models and Adjust Each Network Weights and Constants):* The random training data $d_{TRTR,m}$ are used to trained each $m^{th}$ generated ANN models. The learning cycle of ANN algorithm is as shown in Figure 7.

*Step 4.1 (Generate Random Parameters in Each ANN Model):*

In this step, parameter is randomly generated in each ANN model in the beginning, including the weighting vector $\omega_{m,j,g}$ and the constant $\theta_{m,g}$ of neural nodes. These randomly generated parameters will be revised in the following training steps.

*Step 4.2 (Input Training data to Each ANN Model and Calculate the Prediction Output):* Each random record of training data $d_{TRTR,m}$ are used to train each $m^{th}$ previous generated artificial neural network models. Each neural node applies an activation function (i.e. Sigmoid Function) to its input, as shown in (7) and [2, Eq. (8)]:

$$f(net_{m,g}) = f\left(\sum \omega_{m,j,g} x_{m,i} + \theta_{m,g}\right), \tag{7}$$

$$o_{m,g} = \frac{1}{1+e^{-net_{m,g}}}, \tag{8}$$

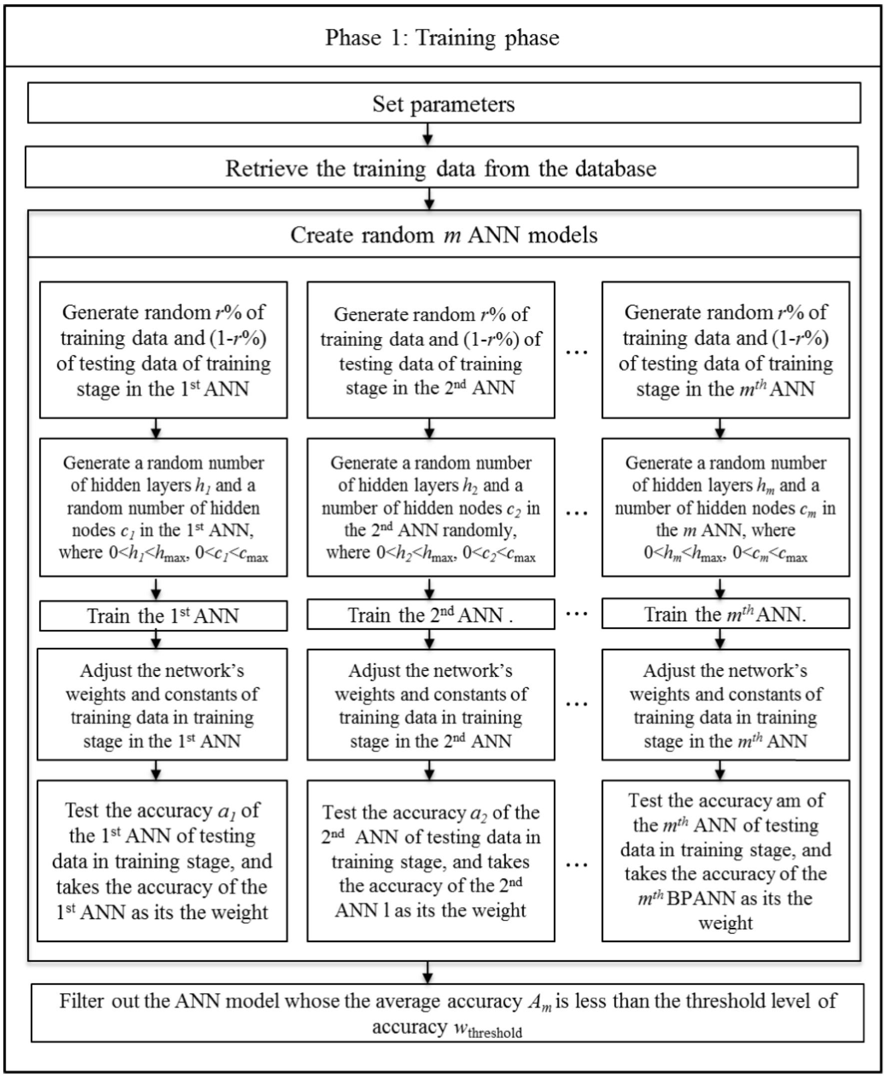


**FIGURE 5. The training phase of the proposed algorithm.**

where $\omega_{m,j,g}$ is the randomly generated weight vector of each neuron, $\theta_{m,g}$ is the randomly generated constant of the hidden layers nodes and output layer nodes, and $o_{m,g}$ is the output vector.

*Step 4.3 (Error-Correction Learning):* The most common error function minimized in neural networks is the sum of squared errors [2]. The error value is backward passed to each neuron and appropriately adjusts weights and constants so as to minimize the error in its predictions, as shown in Eq. (9), Eq. (10), Eq. (11) and [10, Eq. (12)].

The error of the neuron of output layer:

$$E_{m,g} = o_{m,g}(1 - o_{m,g})(t_{m,g} - o_{m,g}), (9) \tag{9}$$

where $t_{m,g}$ is the target output, the function $E_{m,g}$ is the computed output error at neuron $g$.

The error of the neuron of hidden layer:

$$E_{m,j} = o_{m,g}(1 - o_{m,g})E^*_{m,g}\omega_{m,j,g}, \tag{10}$$

$$\omega_{m,j,g} = \omega_{m,j,g} + \eta^* E^*_{m,g} o_{m,j}, \tag{11}$$

$$\theta_{m,g} = \theta_{m,g} + \eta^* E_{m,g}, \tag{12}$$

Where $t_{m,g}$ is the target output, the function $E_{m,g}$ and $E_{m,j}$ are the computed output errors at neuron $g$ and $j$, $\omega_{m,j,g}$ is the weight, $\theta_{m,g}$ is the constant and $\eta$ is learning rate.

*Step 4.4 (Repeat Step 4.2 to Step 4.3 for the Convergence of the ANN):* With convergence of the network, Step 4.2 to Step 4.3 are repeated until the difference between the output of current iteration and previous one is less than the threshold level $T_{threshold}$.

*Step 5 (Test the Accuracy of ANN of Testing Data in Training Phase):* After training all of ANNs, the performance of ANN is validated by the rest of (1-$r$) testing data $d_{\mathrm{TETR},m}$ in training phase. In addition, the average accuracy $A_m$ of each ANN is calculated as the weight of each ANN.

*Step 6 (Filter Out the ANN):* These average accuracy $A_i$ of the ANN is compared with the accuracy threshold $w_{threshold}$.

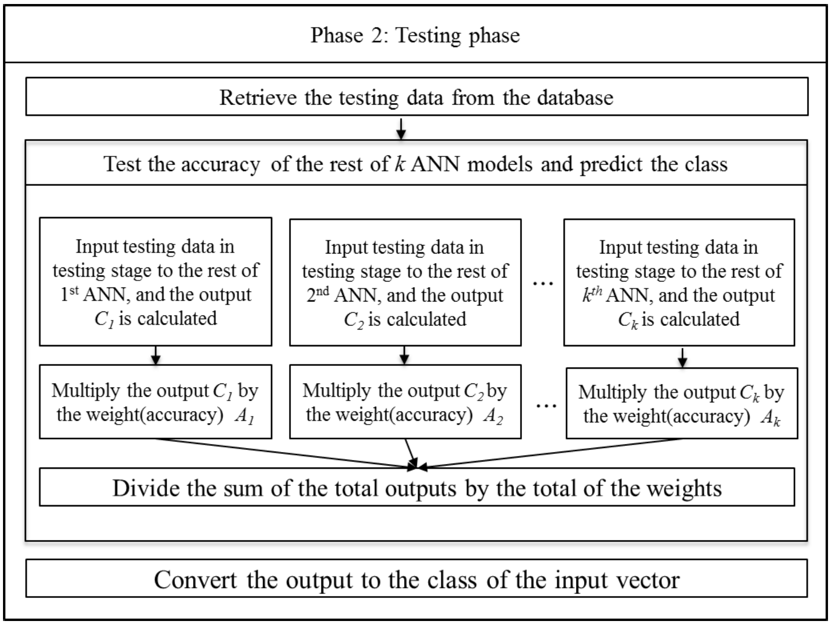


**FIGURE 6.** **The testing phase of the proposed algorithm.**

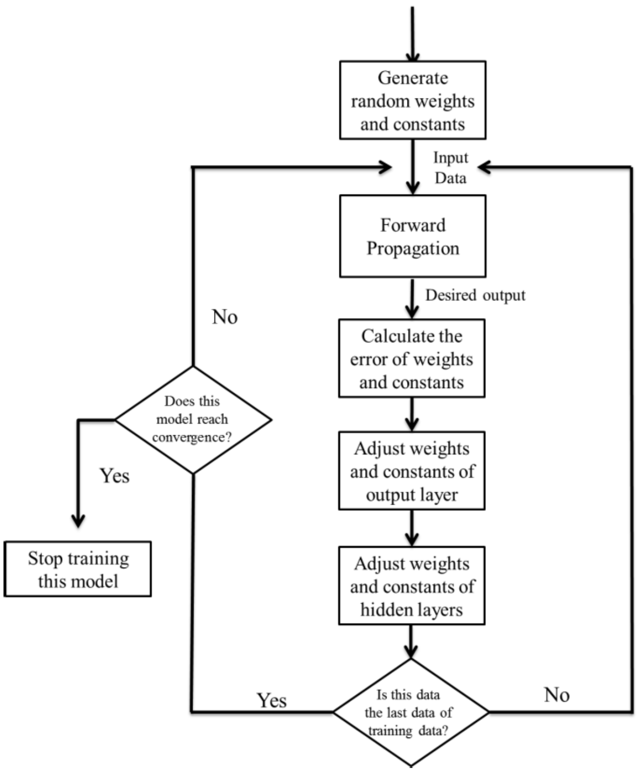


**FIGURE 7.** **The learning cycle of artificial neural network.**

If the average accuracy $A_m$ of the $m^{th}$ ANN is less than the threshold level of accuracy $w_{threshold}$, its network will be filter out (i.e., the pruning phase and the combining phase for ENNs). However, the rest of $K$ ANN models with higher accuracy would be used to validate and test in the following testing phase.

**TABLE 3.** **Programming language and implementation platform of the AR-QAS.**

| | | |
|---|---|---|
| **Programming language** | 1. | Java |
| **Implementation Device** | 1. | ASUS Eee Pad Transformer Prime (TF201) |
| **Implementation Hardware** | 2.<br>3.<br>4.<br><br>5. | Chipset: NVIDIA Tegra 3<br>CPU: Quad-core CPU<br>Internal Memory: 1GB RAM<br>Camera: CMOS 8MP Rear |
| **Implementation Software** | 1.<br>2. | Android 4.1.1<br>QCAR |

## C. PHASE 2: TESTING PHASE

In this phase, the proposed algorithm uses the testing data $d_{TE}$ to valid the remaining $K$ ANN models, and predict the class.

*Step 1: (Retrieve the Testing Data From the Database):* In testing phase, the testing data $d_{TE}$ are retrieved for the prediction.

*Step 2: (Predict the Class of the Input Data):* The testing data $d_{TE}$ in testing phase are inputted to $K$ ANN models from training phase. The output $C_k$ can be calculated by each $k^{th}$ ANN model and each $C_k$ can be multiplied by the corresponding weighting value $A_k$ of the $k^{\mathrm{th}}$ ANN model. Then a weighted average of the sum of total weighted outputs can be obtained.

*Step 3 (Convert the Output to the Class of the Input Vector):* After predicting the weighted average of input data from $K$ ANN models, the predicted output can be converted into the predicted class.

**TABLE 4.** The 20 questions designed in this study.

| ID | Question (in Chinese) | Phonetic transcription by Google translator | Question (in English) |
|---|---|---|---|
| Q1 | 捷運板南線有哪幾站？ | Jié yùn b ǎ n nán xiàn y ǒ u n ǎ j ǐ zhàn | Which stations belong to the Bannan Line? |
| Q2 | 微風廣場在哪一站？ | Wéifē ng gu ǎ ngch ǎ ng zài n ǎ yí zhàn | Which station is closest to the Breeze Center? |
| Q3 | 桐花節要去哪裡看花？ | Tóng huā jié yào qù n ǎ l ǐ kàn huā | How do I get to the Hakka Tung Blossom Festival? |
| Q4 | 東區是在哪一站捷運站？ | Dō ngqū shì zài n ǎ yí zhàn jié yùn zhàn | Which stations are within the “Eastern area” of Taipei city? |
| Q5 | 五分埔怎麼走比較方便？ | W ǔ fēn bù zěnme z ǒ u b ǐ jiào fāngbiàn | How do I get to Wufenpu Garment Wholesale Area in a shortest way? |
| Q6 | 華山藝文特區現在有什麼展覽活動？ | Huàshā n yì wén tèqū xiànzài y ǒ u shé me zh ǎ nl ǎ n huódòng | What are the exhibitions in Huashan now? |
| Q7 | 板橋火車站附近有什麼好吃的美食？ | B ǎ nqiáo hu ǒ chē zhàn fùjìn y ǒ u shé me hào chī dì měishí | Is there any food recommended around the Banqiao Station? |
| Q8 | 捷運板南線末班車是幾點？ | Jié yùn b ǎ n nán xiàn mòbānchē shì j ǐ di ǎ n | What time is the last MRT of Bannan Line? |
| Q9 | 如何從台北車站轉搭其他的捷運線？ | Rúhé cóng táiběi chē zhàn zhu ǎ n dā qítā de jié yùn xiàn | How can I transfer to the other lines in Taipei Main Station? |
| Q10 | 東區地下街範圍多大？ | Dō ngqū dìxiàjiē fànwéi duō dà | How big is the region of East Metro Mall? |
| Q11 | 從臺北火車站到南港要多久？ | Cóng táiběi hu ǒ chē zhàn dào náng ǎ ng yào duōji ǔ | How long will it take from Taipei Main Station to Nankang Station by MRT? |
| Q12 | 3C 產品壞了要去哪裡修？ | 3C ch ǎ np ǐ n huàile yào qù n ǎ l ǐ xiū | Where can I fix the 3C products? |
| Q13 | 南港展覽館通常都在舉辦什麼樣的活動？ | Náng ǎ ng zh ǎ nl ǎ n gu ǎ n tōngcháng dōu zài j ǔ bàn shénme yàng de huódòng | What kinds of activity are mostly held in Nangang Exhibition Hall? |
| Q14 | 101 大樓有多高？ | 101 Dàlóu y ǒ u duō gāo | What is the height of Taipei 101? |
| Q15 | 信義威秀現在有什麼電影可以看？ | Xìnyì wē i xiù xiànzài y ǒ u shé me diàny ǐ ng kěy ǐ kàn | What movies are playing in Vie Show Cinema? |
| Q16 | 哪裡有誠品書店？ | N ǎ l ǐ y ǒ u chéng p ǐ n shūdiàn | Where are the Eslites Bookstores? |
| Q17 | 搭捷運要注意什麼？ | Dā jié yùn yào zhùyì shénme | What safety rules should I follow when I’m taking the MRT? |
| Q18 | 國父紀念館的簡介為何？ | Guófù jìniàngu ǎ n de ji ǎ njiè wèihé | What is the introduction of Sun Yat-sen Memorial Hall? |
| Q19 | 臺北有什麼名產可以買？ | Táiběi y ǒ u shé me míngch ǎ n kěy ǐ m ǎ i | What are the local specialty products of Taipei City? |
| Q20 | 哪裡有電影院？ | N ǎ l ǐ y ǒ u diàny ǐ ngyuàn | What stations have cinemas nearby? |

## IV. EVALUATION AND EXPERIMENTAL RESULTS

In this section, the experimental environment is presented first. The programming language and implementation platform are shown in the beginning. Second, the design of experiment is introduced. A simple and active example of using the proposed AR-QAS is given at last to leave deeper impression to the readers. Third, a case study is given for the demostation of the proposed AR-QAS. Finally, the experimental results are analyzed and discussed.

**FIGURE 8.** A guiding flyer of Taipei MRT-Bannan Line.

### A. EXPERIMENTAL ENVIRONMENT

The AR-QAS is implemented by Java language. The AR-QAS in this study is a program as an application and runs on the mobile devices which use Android operating system. The information about programming language and implementation platform of the AR-QAS is in detail in Table 3. In addition, the classification method of the AR-QAS is implemented by R language. The version of R language is 0.98.501 issued by RStudio, Inc. from 2009 to 2013. Moreover, QCAR (Qualcomm Augmented Reality) APIs (Application Programming Interfaces) are applied for the implementation of AR functions in the proposed system.

### B. EXPERIMENT DESIGN

In this study, 20 questions were designed, as shown in Table 4. 30 users, who are 15 men and 15 women, had participated in the experiment and were asked the 20 questions. 600 collected sentences were produced in the experiment. Moreover, this study used k-fold cross-validation [21] to measure the performance of the AR-QAS. Training and testing were executed 20 times (i.e., k = 20). In iteration, collected sentences were selected as the test corpus. Therefore, the test corpus would have only one collected sentence of each suggested question in each iteration. The rest of the collected sentences were then used in the training phase to train the system for the values provided by each question.

### C. CASE STUDY

A guiding flyer of Taipei MRT-Bannan Line introduces some Hot Spot in Taipei, as shown in Figure 8. User can use their camera on the mobile phone at the guiding flyer and scan the image of the flyer. An introduction video is generated by AR technology on the mobile phones, as shown in Figure 9.

Users can touch the screen and start to ask questions. For example, users can ask a question like ''101 大樓有多高 (101 Dàlóu you duō gāo)'' that is ''What is the height of Taipei 101''. The question asked by users is translated to the text by Google speech recognition API and sent to the QAS on the cloud server. After the process of the QAS, the output, that is the answer, is transformed into voice and responded to users by the technique of text-to-speech on mobile phones. In this example, a corresponding answer is provided, ''The height of Taipei 101 is 508 m. The Taipei 101 tower comprises 101 floors above ground and 5 floors underground, and is the fourth highest building in the world''.

**FIGURE 9.** The flow chart of the QAS.

### D. RESULT ANALYSES

This study uses R language for the evaluation of the AR-QAS. This study compared three data mining algorithms (i.e., logistic regression, artificial neural network and random back-propagation neural network) to predict the question. The comparison of four measurement, accuracy, precision, recall and F-measure, among each algorithm is presented in this study.

For the ANN and the proposed algorithm, different architectures were evaluated in each iteration. After that, the architecture with high accuracy was selected. For ANN algorithm, the architecture of ANN with 139 input neurons of input layer, 4 hidden layers, 10 neurons of first hidden layer, 30 neurons

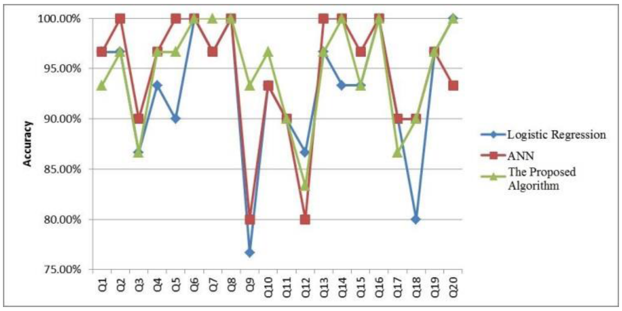


**FIGURE 10.** **Comparison of accuracy among logistic regression, ANN and the proposed algorithm.**

of second hidden layer, 20 neurons of third hidden layer, 10 neurons of fourth hidden layer and 1 neuron of the output layer results in the highest accuracy of 94.50% among other architecture of ANNs. For the proposed algorithm, the architecture of the proposed algorithm includes 139 input neurons of input layer, 10 random neural networks, maximum 4 of hidden layer of each network, maximum 30 of neurons of each hidden layer, the weight threshold of 93% and 1 neuron of the output layer results in the highest accuracy of 94.83% among other parameters of the proposed algorithm.

The comparison of accuracy among logistic regression, ANN and the proposed algorithm is presented in Figure 10. The average accuracies of logistic regression, ANN, and the proposed algorithm are 92.83%, 94.50%, and 94.83%, respectively. The experimental results show that the accuracy of the proposed algorithm is superior to the other two methods and is suitable for this case study.

## V. CONCLUSION AND FUTURE WORK

In the last section of this study, a review of the contribution of this paper is presented first. The future work and improvement are given at the end of this study.

### A. CONCLUSIONS

This study designs an augmented reality question answering system (AR-QAS) on mobile devices to apply and implement the proposed algorithm. AR-QAS can offer user active interaction and automatically reply according to user's queries [3] The AR-QAS receives input requirement form the users and responds with the appropriate classes of the input queries which are accurate answers to the users.

In our experiment, the logistic regression retains the accuracy of 92.83%, the precision of 93.13%, the recall of 92.83%, and the $F$-measure of 92.79%. The ANN has the accuracy of 94.50%, the precision of 94.76%, the recall of 94.50%, and the $F$-measure of 94.45%. Our proposed algorithm possesses the accuracy of 94.83%, the precision of 94.98%, the recall of 94.83%, and the $F$-measure of 94.81%. The result demonstrates that the performance of the proposed algorithm, which can filter out the incorrect ANN models, is the best. In consequence, the proposed algorithm can be utilized to the implemented AR-QAS in the similar applications.

### B. FUTURE WORK

As mentioned in Section 3.2, the proposed algorithm is restricted by the failure of time complexity. Therefore, future researchers can evaluate the importance of accuracy and the consumed times in order to find the appropriately data mining method. Meanwhile, as data mining has drawn much attention, how to find the appropriately data mining method to turn the data into the useful information and knowledge in different fields is the important topic in recent years. However, in this study, the proposed algorithm is implemented in augmented reality question answering system. The proposed algorithm can apply to many other areas in the future to valid that whether the proposed algorithm is better than existing ANN algorithm in different fields.

In the case study of AR-QAS, the proposed algorithm was applied to resolve the classification problems of QAS for the analyses of users' queries. However, this study implemented QCAR APIs to perform image recognition and provide AR services without our own technology. In the future, the proposed algorithm can be used to recognize images for the applications of AR.

## REFERENCES

[1] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd ed. San Francisco, CA, USA: Morgan Kaufmann, 2011.

[2] I. McLoughlin, H. Zhang, Z. Xie, Y. Song, and W. Xiao, "Robust sound event classification using deep neural networks," *IEEE/ACM Trans. Audio, Speech, Language Process.*, vol. 23, no. 3, pp. 540–552, Mar. 2015.

[3] L. Hirschman and R. Gaizauskas, "Natural language question answering: The view from here," *Natural Lang. Eng.*, vol. 7, no. 4, pp. 275–300, 2001.

[4] C. M. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2006.

[5] D. W. Hosmer, S. Lemeshow, and R. X. Sturdivant, *Applied Logistic Regression*, 3rd ed. Hoboken, NJ, USA: Wiley, 2013.

[6] J. Wang, C. Man, Y. Zhao, and F. Wang, "An answer recommendation algorithm for medical community question answering systems," in *Proc. IEEE Int. Conf. Service Oper. Logistics, Informat.*, Beijing, China, Jul. 2016, pp. 139–144.

[7] Q. Wu, C. Shen, P. Wang, A. Dick, and A. van den Hengel, "Image captioning and visual question answering based on attributes and external knowledge," *IEEE Trans. Pattern Anal. Mach. Intell.*, to be published, doi: 10.1109/TPAMI.2017.2708709.

[8] A. Abraham, "Artificial neural networks," in *Handbook of Measuring System Design*. Hoboken, NJ, USA: Wiley, 2017, doi: 10.1002/0471497398.mm421.

[9] M. Riedmiller and H. Braun, "A direct adaptive method for faster backpropagation learning: The RPROP algorithm," in *Proc. IEEE Int. Conf. Neural Netw.*, San Francisco, CA, USA, Apr. 1993, pp. 586–591.

[10] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representations by error propagation," in *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, vol. 1. Cambridge, MA, USA: MIT Press, 1986, pp. 318–362.

[11] L. K. Hansen and P. Salamon, "Neural network ensembles," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 12, no. 10, pp. 993–1001, Oct. 1990.

[12] A. Krogh and J. Vedelsby, "Neural network ensembles, cross validation and active learning," in *Proc. 7th Int. Conf. Neural Inf. Process. Syst.*, Denver, CO, USA, 1994, pp. 1–8.

[13] Z.-H. Zhou, J. Wu, and W. Tang, "Ensembling neural networks: Many could be better than all," *Artif. Intell.*, vol. 137, no. 1, pp. 239–263, 2002.

[14] P. M. Granitto, P. F. Verdes, and H. A. Ceccatto, "Neural network ensembles: Evaluation of aggregation algorithms," *Artif. Intell.*, vol. 163, no. 2, pp. 139–162, 2005.

[15] D. Lee and R. Baldick, "Short-term wind power ensemble prediction based on Gaussian processes and neural networks," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 501–510, Jan. 2014.

[16] D. R. Berryman, "Augmented reality: A review," *Med. Ref. Services Quart.*, vol. 31, no. 2, pp. 212–218, 2012, doi: 10.1080/02763869.2012.670604.
[17] H. F. Lin and C. H. Chen, "Design and application of augmented reality query-answering system in mobile phone information navigation," *Expert Syst. Appl.*, vol. 42, no. 2, pp. 810–820, 2015.
[18] W. Y. Ma and K. J. Chen, "Introduction to CKIP Chinese word segmentation system for the first international Chinese Word Segmentation Bakeoff," in *Proc. 2nd SIGHAN Workshop Chin. Lang. Process.*, vol. 17. 2003, pp. 168–171.
[19] D. Dubin, *The Most Influential Paper Gerard Salton Never Wrote*. Library Trends, vol. 52. 2004, pp. 748–764.
[20] H. Wu, R. Luk, K. Wong, and K. Kwok, "Interpreting TF-IDF term weights as making relevance decisions," *ACM Trans. Inf. Syst.*, vol. 26, no. 3, 2008, Art. no. 13.
[21] R. Kohavi, "A study of cross-validation and bootstrap for accuracy estimation and model selection," in *Proc. 14th Int. Joint Conf. Artif. Intell. (IJCAI)*, vol. 2. 1995, pp. 1137–1143.

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