Classifying inpatient perception of hospitalization experience across the US 50 states using the convolutional neural networks

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Abstract

Backgrounds The grade of hospital-service quality is required for the classification which is never applicable in the literature. We aimed to classify the grade of inpatients' perceptions of patients' hospitalization experience of states in the US using convolutional neural networks(CNN).Methods We downloaded HCAHPS (Hospital Consumer Assessment of Healthcare Providers and Services) data from the 2007-2014 summaries of survey results. The data collection was carried out to the k-mean and the CNN that were used as unsupervised and supervised learnings for (1) dividing the US sates into two classes (n = 19 and 32 of lower and higher grades) and (2) building a hospital service predictive model to estimate 38 parameters. We calculated the sensitivity, specificity, and receiver operating characteristic curve [area under the curve (AUC)] across studies for comparison. An app predicting the hospital service for a specific US state was developed involving the model's 38 estimated parameters for a website assessment.

Results We observed that (1) the two-year 20-item model yields a higher accuracy rate (0.98) with an AUC (0.99; 95% CI 0.95–1.00) based on the 51 states; and (2) an available app for predicting hospital-service quality was successfully developed and demonstrated in this study. A smartphone app was designed to classify the grade of hospital service for each US state.

Conclusions The 20-item model with the 38 parameters estimated by using CNN for improving the accuracy of the grade about the inpatients' perceptions of patients' hospitalization experience of states in the US for hospital service. An app developed for helping patients' self-assess hospital service quality in each US state is required for application in the future.

Highlights

- We developed an App in use for assessing the quality of hospital service in the US states.
- The CNN algorithm was used in this study, particularly in MS Excel, which is rarely seen in the literature.
- A dashboard on Google maps successfully reports inpatient perception of hospitalization experience across US 50 states.
- A smartphone APP was designed to get feedback directly from patients' perceptions of hospitalization experience.

Introduction

The quality of health care is always an important topic we concern about in the medical settings, especially in the age that the patient involvement is appearing increasingly on the policy and action agendas of health care providers [1]. There are many ways to report healthcare quality to the public. However, those professional indicators are unfamiliar to patients when using a static table or image format which is hard to know where to get the best care [2-6].

The England Picker Institute Europe (EPIE) [7] and the Hospital Consumer

Assessment of Healthcare Providers and Services (HCAHPS) [8] are two famous

examples of periodically assessing patient expectations of hospital healthcare, experience, and satisfaction, and of publicly reporting their perceptions of their experience and whether they were satisfied [9-11]. From which, Picker's item-by-item box plots of disclosure and the HCAHPS hospital characteristics comparison charts are the addition to the summary analysis page on their respective web sites. Whether an app for classifying the grade of hospital service can be used in healthcare settings is required to develop.

The convolutional neural networks(CNN) has had the greatest impact within the field of health informatics [12]. Its architecture can be described as an interleaved set of feedforward layers implementing convolutional filters followed by reduction, rectification, or pooling layers [13–15]. For each layer, the CNN creates a high-level abstract feature. Whether the CNN, a famous deep learning method, can improve the prediction accuracy (up to 7.14 %) [15] on hospital service classification is worthy of study.

Google Maps provide an overall view of geospatial visualization with coordinates of latitude and longitude on a map [16,17]. However, few were found in Pubmed Central(PMC) using a keyword google map in the title to search on December 12, 2019. An easy way with an application programming interface (API) [17] technique to help hospital practitioners quickly set up an assessment system for patient quality of healthcare is needed to explore.

Furthermore, the HCAHPS survey consists of ten domains in comparison each year for the same states in the US. The grade of classification in hospital service quality is expected to demonstrate in healthcare practice.

The aim of the current study was thus to investigate (1) whether the inpatients' perceptions of patients' hospitalization experience of states in the US can be graded and classified, (2) what type of API that can help us quickly build up an online method for displaying survey results on Google Maps, and (3) how to demonstrate an online assessment that uses smartphones for classifying the grade of the US state according patients' perceptions of their hospitalization experience.

Methods

Study Data

We downloaded data (Summary Analysis of HCAHPS survey results: January 2007 to December 2014) Discharges of inpatient perceptions of their hospitalization

experience across 51 US states (includes Washington, DC) at the HCAHPS website [8]. The freely available spreadsheet there includes 10 dimension scores (range: 0-100 [higher is better]) consisting of

the following: (1) Communication with Nurses, (2) Communication with Doctors, (3) Responsiveness of Hospital Staff, (4) Pain Management, (5) Communication about Medicines, (6) Cleanliness of the Hospital Environment, (7) Quietness of the Hospital Environment, (8)Discharge Information, (9) Overall Hospital Rating, and (10) Recommendation of the Hospital.

Featured variables

Featured variables consist of two-year 20 items(=20itmes * 2 years) in 2013 and 2014 used for classifying the binary grade(i.e., low and high levels). The 51 US states were used in this study. The data are shown in Additional File 1.

All data used in this study were downloaded from HCAHPS. This means that ethical approval is not necessary for the study, in accordance with the regulation promulgated by the Taiwan Ministry of Health and Welfare.

Unsupervised and supervised learnings

Unsupervised learning indicates agnostic aggregation of unlabeled data sets yielding groups or clusters of entities with shared similarities that may be unknown prior to the analysis step [18,19] (e.g., clustering dimensionality reduction using principal component analysis or *k*-mean clustering). The *k*-mean clustering aims to partition *n* observations into *k* clusters, in which each observation belongs to the cluster with the nearest mean [20].

In contrast, supervised learning employs “labeled” training data sets (labeled/supervised by subject experts or by the objective *k*-mean clustering) to yield a qualitative or quantitative output [19,21].

In this study, the *k*-mean was used as unsupervised learning for (1) clustering the US states into two classes (n = 19 and 32 of lower and higher grades). CNN was applied as supervised learning to build a prediction model for estimating the 38 parameters. See the next section for detailed information.

CNN applied to this study

CNN is a variant of the standard multilayer perceptron, especially used for pattern recognition compared with conventional approaches [22] due to its capability in reducing the dimension of data, extracting the feature sequentially, and classifying one structure of the network [23]. The basic CNN model was inspired in 1962, from the visual cortex proposed by Hubel and Wiesel [22].

For simplifying the CNN concept and process, we present it in Microsoft Excel in Figure 1. The detailed information on interpretation is provided in Additional File 2 for interested readers.

===Figure 1 inserted here===

Tasks for performing CNN

- ***Task 1: building the predictive model and estimate the model parameters***

The 20 featured variables on 51 cases were mirrored to compare the prediction accuracies {e.g., the sensitivity, specificity, and receiver operating characteristic (ROC) curve [area under the curve (AUC)]} using the CNN algorithm.

Different from the traditionally predictive method, we use the known responses (i.e., the 20 items for each US state) and their corresponding labels (i.e., the binary grade, low and high in service quality) to build a model for predicting the unknown label of the specific responses. The latter step is to estimate the 38 model parameter using the Solver Add-in function in Microsoft Excel, see Additional File 3.

- ***Task 2: App classifying the grade of hospital service for a web-based assessment***

A 20-item assessment app using patient mobile phones was designed to classify the grade for each US state using the CNN algorithm and the model parameters. The resulting classification appears on smartphones. The visual representation with binary category probabilities is shown on a dashboard using Google Maps to display using the Rasch rating scale model[24].

Visual displays using choropleth maps

Choropleth maps(CM) have been applied to the use of the disparities in health outcomes across areas in many disciplines[25]. The US map was created and colored by the two grades predicted using the CNN model.

Statistical tools and data analysis

MedCalc 9.5.0.0 for Windows (MedCalc Software) was used to calculate the sensitivity, specificity, and corresponding AUC using logistic regression when the observed labels(i.e., 0 for the low grade and 1 for the high grade) and the predicted probabilities (i.e., the continuous variable in step 3 calculated by the sigmoid function in the output layer in Figure 1) were applied. Analysis of variance was performed to examine the difference between the two predicted groups(i.e., the low and high grades)

A visual representation displaying the classification effect is plotted using two curves(i.e., one from the left-bottom to the right-top corner denotes the success(i.e., the high grade) feature and another from the left-top corner to the right-bottom side as the failure attribute) [24]. The study flowchart and the CNN modeling process are shown in Figure 2 and Additional File 2, respectively.

===Figure 2 inserted here===

Results

The US states were dividing into two classes (n = 19 and 32 of lower and higher grades) using k-mean method. A significant difference was found ($p<0.05$, $F(1,49)=75.229$) in two groups(i.e., the low and high grades). Two states with false positive and false negative, respectively, are states North Dakota(MD) and Oregon(OR), see Figure 3.

The two-year 20-item CNN model yields a higher accuracy rate (0.98) with an AUC (0.99; 95% CI 0.96–1.00) based on the 51 cases. Only one state with false negative is Minnesota(MN) resulting in the specificity at 0.95(Table 1).

===Table 1 inserted here===

An online dashboard was designed to report patient perceptions of the inpatient hospitalization experience by grade labels on Google Maps. It is easy to see where are with better hospital-service quality using the HCAHPS survey results in 2013 and 2014. Interested readers are invited to scan the QR-code on Figure 4 and see the details about more information while the state of interest is clicked.

===Figue 3 and 4 inserted here===

An available app for predicting hospital-service quality was successfully developed and demonstrated in Figure 5. A smartphone app was designed to classify the graded of hospital service for each US state. The website can be linked by scanning the QR-code on Figure 5. In this case, the high-quality grade (class 2) is responded to by the CNN algorithm. The curve from the left-bottom corner to the right-top side represents the correctness as a student answers a specific item.

===Figue 5 inserted here===

Discussion

We observed that (1) the two-year 20-item model yields a higher accuracy rate (0.98) with an AUC (0.99; 95% CI 0.95–1.00) based on the 51 states; and (2) an available app for predicting hospital-service quality was successfully developed and demonstrated in this study. A smartphone app was designed to classify the grade of hospital service for each US state.

There were many surveys about patient experience in the hospital. Most of them were administered by postal mail, and response rates varied widely, from very low to relatively high [26]. The US HCAHPS 2013 survey(Additional File 4) showed the average response rate was 32% [8]. The first public report was in 2008. By contrast, the England NHS led the way internationally in mandating a national patient survey program in 2001[27]. The Picker Institute [7] has a number of survey tools targeted towards patient experience, for use both within and outside hospitals. An increasing number of people are using the Internet as a platform to describe their healthcare in the UK [28]. Similarly, in the US, more than eight out

of 10 adults are using the Internet regularly [29]. However, no such an online classification of hospital-service quality was developed as we did in the literature.

Furthermore, smartphones are becoming ubiquitous [30-31]. It is time to develop a module that can show the survey results using dashboards to display on Google Maps. The reason is attributable not only to the study [27-32] reporting the web-based online ratings correlated well with the traditional national survey and had similar response rates but also to the very solicited survey of patient experience feedback sent by the hospital. It may be useful tools for patients who responded to the survey in a hope to see the results with a visualized representation as we designed in Figure 5. However, no such a convenient tool (i.e., incorporating Google maps with smartphones) was found to show the classification results of inpatient perception of hospitalization for the US states in previous papers.

CNN can improve prediction accuracy (up to 7.14%) [15]. It is worth noting that the CNN is not based on the traditional cutting point(two case missed in Figure 3) and increases the prediction accuracy(one case missed in Table 1). We have not seen anyone using the CNN approach to predict patients' perceptions of their experiences in hospitalization, which is a breakthrough, and the first feature of this study.

Over 708 articles have been found using the keyword "convolutional neural network" [Title] searched in PubMed Central as of September 23, 2019. None used Microsoft Excel to perform the CNN. The interpretations for the CNN concept and the process or even the parameter estimations are shown in Figure 1 and Additional File 2, which is the second feature of this study.

Using Microsoft Excel to perform CNN is the third feature of this study, see Additional File 2 and 3, which was rarely seen applicable in the literature.

Furthermore, the curves of category probabilities based on the Rasch rating scale model[24] were shown in Figure 4. The binary categories (e.g., success and failure on an assessment in the psychometric field) have been applied in health-related outcomes[33-38]. However, none provided the animation-type dashboard on Google Maps, as we did in Figure 5.

Strengths Of This Study

We entirely applied the CNN algorithm along with the model's parameters to design the routine on an app that is used to classify the grade for the hospital-service quality in the US states (see Figure 5), which has never been seen before implemented on mobile phones.

As with all forms of web-based technology, advances in health communication technology are rapidly emerging [39]. The mobile online assessment is promising and worth considering in many fields of health assessment. Interested readers are recommended to scan the QR codes on Figure 5 and see (1) the details about the process we provided in this study or (2) the real experience on copy and paste the 20-item score for anyone state on this website assessment.

The CNN module on Microsoft Excel is unique, see Additional File 2 and 3. Users who are not familiar with the CNN software (e.g., Python) can apply our Excel-VBA module to conduct CNN-related research. The module is not limited to the binary classification. The multi-classification module can be done by adding the layers on CNN. That is, two categories require two input layers and two pooling layers. Similarly, three categories need three input layers and three pooling layers, see Figure 1 and Additional File 2 and 3. Any other types of self-assessment, such as work bully, depression, and dengue fever, can apply the CNN model to predict and classify the grades of harmfulness and disease in the future.

Limitations And Suggestions

There are several limitations to this study. First, the data were extracted from the HCAHPS website, see Additional File 1. It is worth noting that any generalization should be made in a similar feature based on the healthcare service and the period being investigated. More studies are required to verify the quality of care provided by US states in the future.

Second, we downloaded study data from a website for the scores (from 0 to 100) of the HCAHPS survey which were not the original responses from patients. Future studies are recommended to use the first-hand data from patients if possible to yield more precise results about the inpatient experience of hospitalization to maintain the whole information in the analysis.

Third, a dashboard is not limited to the one we provided in Figures. Many other types of dashboards are needed to develop on the internet in the future.

Fourth, we recommend additional studies using their own unsupervised algorithm for classifying groups instead of k-mean used in this study and then using the CNN model or others to estimate the parameters in the future.

Conclusion

We illustrate features and contributions in this study: (1) CNN performed in Microsoft Excel, (2) dashboards on Google Maps applied to increase the comprehensiveness and readability on smartphones, (3) an online app demonstrated to display results using visual dashboards, and (4) the category probability curves based on Rasch rating scale model first observed in the CNN prediction model. The novelty of the app with the CNN algorithm improves the predictive accuracy of hospital perceptions on hospitalization for each US state. It is expected for helping hospital administrators self-assess the service grade for their hospitals in the US state.

Abbreviations

API: application programming interface

AUC: Area under ROC curve

CI: confidence intervals

CNN: convolutional neural network

EPIE:The England Picker Institute Europe

FNR: false-negative rate;

HCAHPS: Hospital Consumer Assessment of Healthcare Providers and Services

ROC:Results: a receiver-operating characteristic

VBA:visual basic for application

Declarations

Ethics approval and consent to participate

Not applicable.

All data are publicly come from HCAHPS website.

Consent to publish

Not applicable.

Availability of data and materials

All data used in this study is available in Additional files.

Competing interests

The authors declare that they have no competing interests.

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Authors' Contributions

DH conceived and designed the study, WC, PH and TW interpreted the data, and PH monitored the process and the manuscript. TW drafted the manuscript. All authors read the manuscript and approved the final manuscript.

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Additional files

Additional file 1:

Xls. The study dataset

Additional file 2:

CNN using MS Excel to interpret on Figure 1

Additional file 3:

MP4. The online responding system in Figure 4 and the CNN introduction

https://youtu.be/tb3uFR9_Qmw

Additional file 4:

PDF. The US HCAHPS inpatient experience questionnaire

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Figures

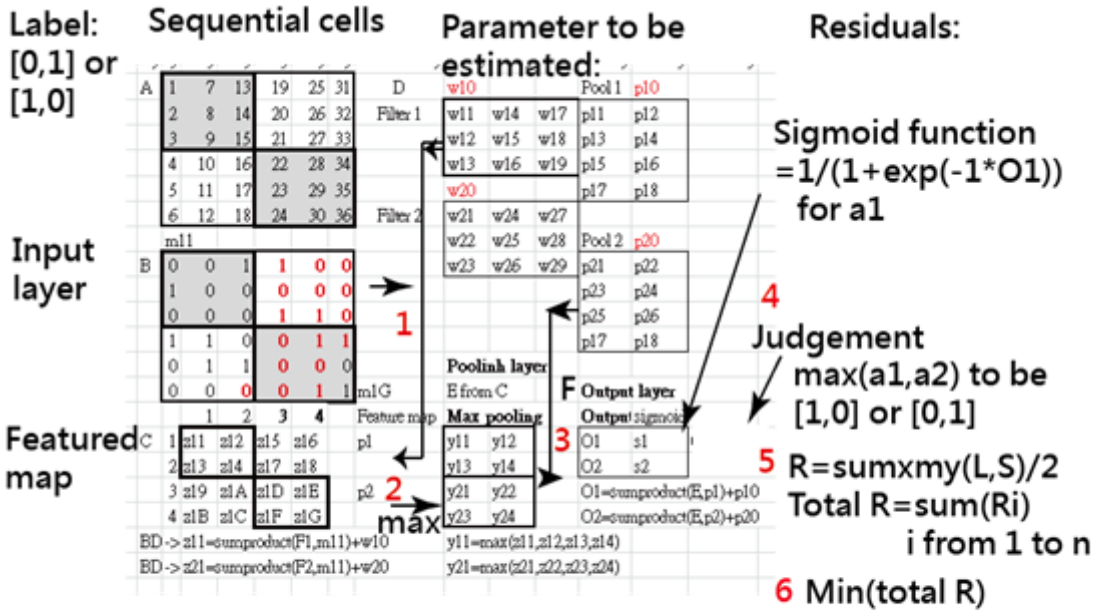

Figure 1

Interpretation of the CNN algorithm in Microsoft Excel.

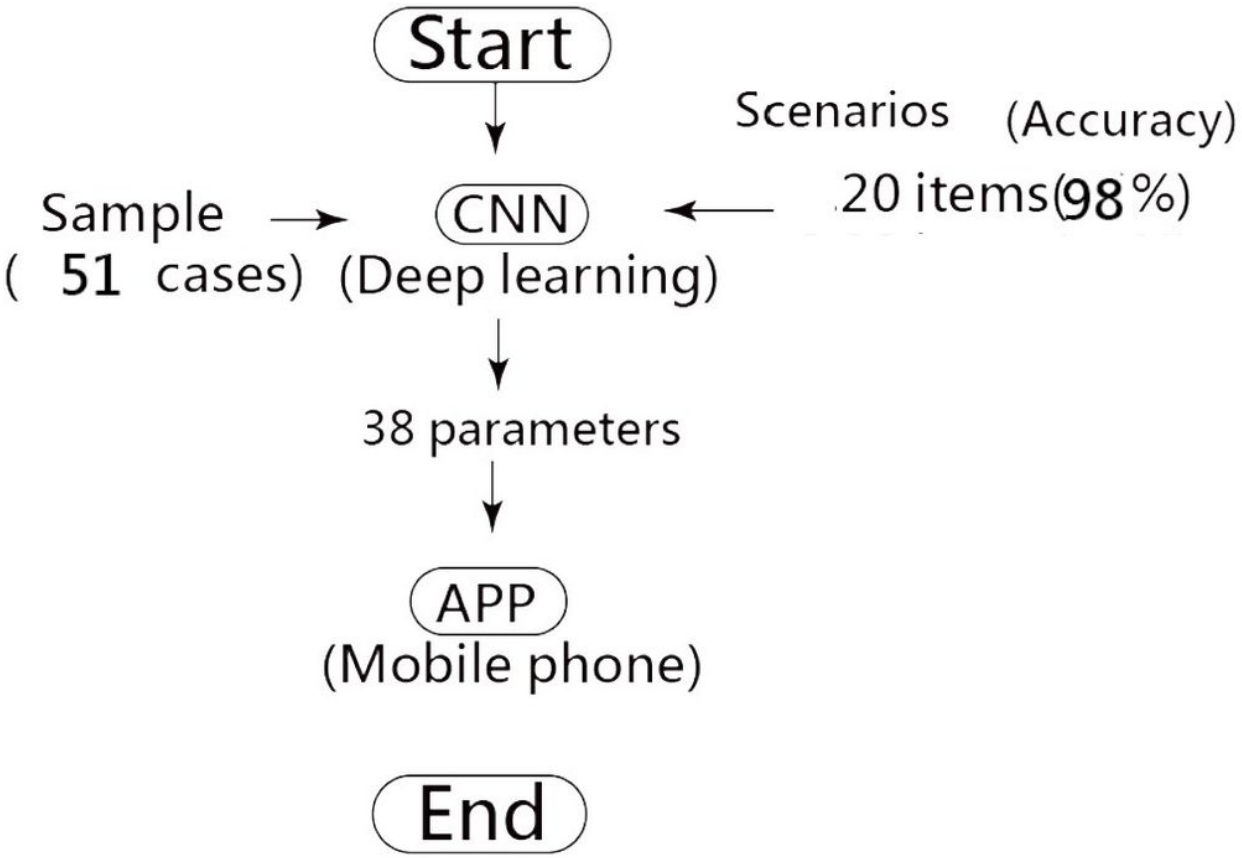

Figure 2

The study flowchart.

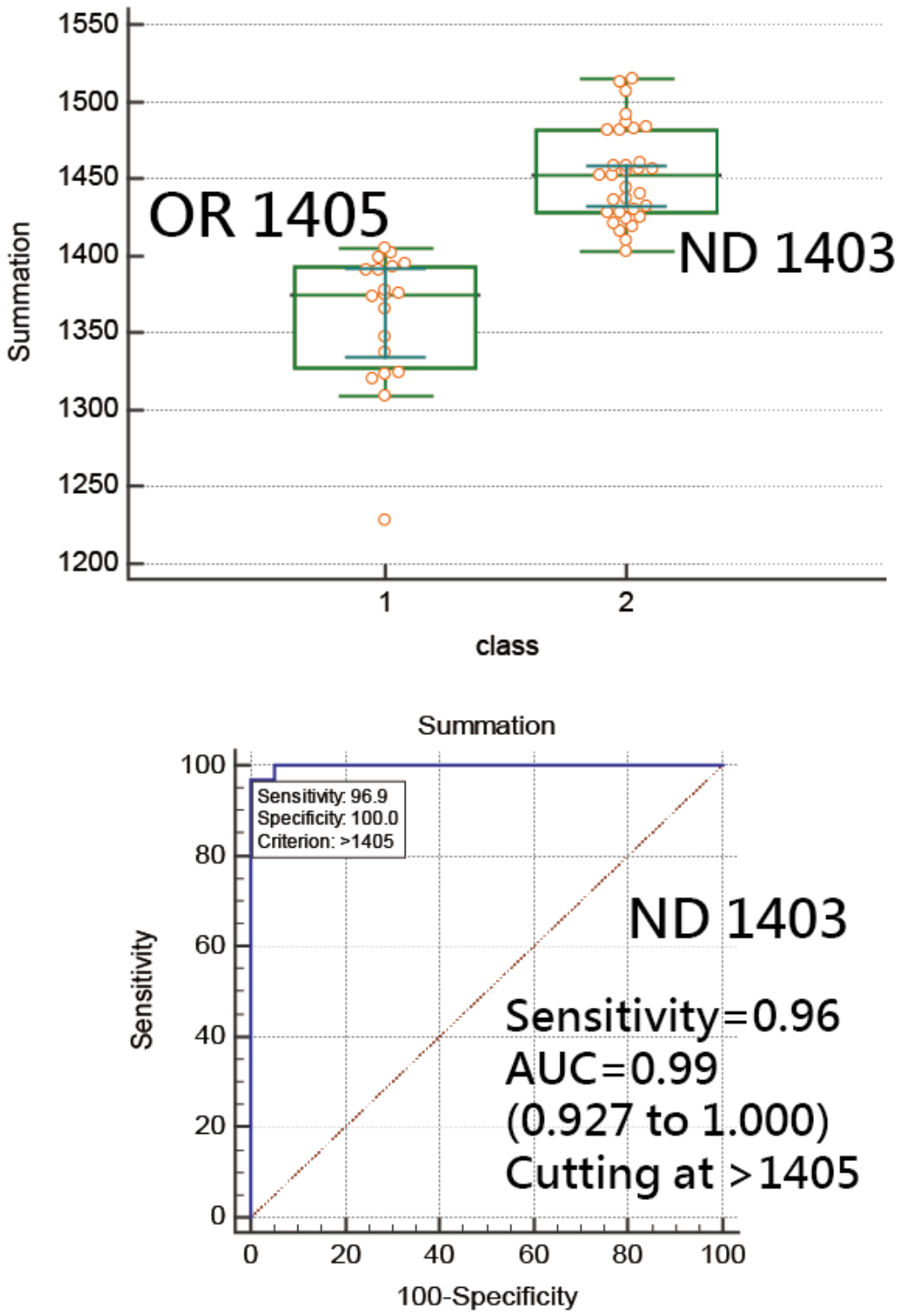

Figure 3

The classification of hospital-service quality in US states using k-mean method

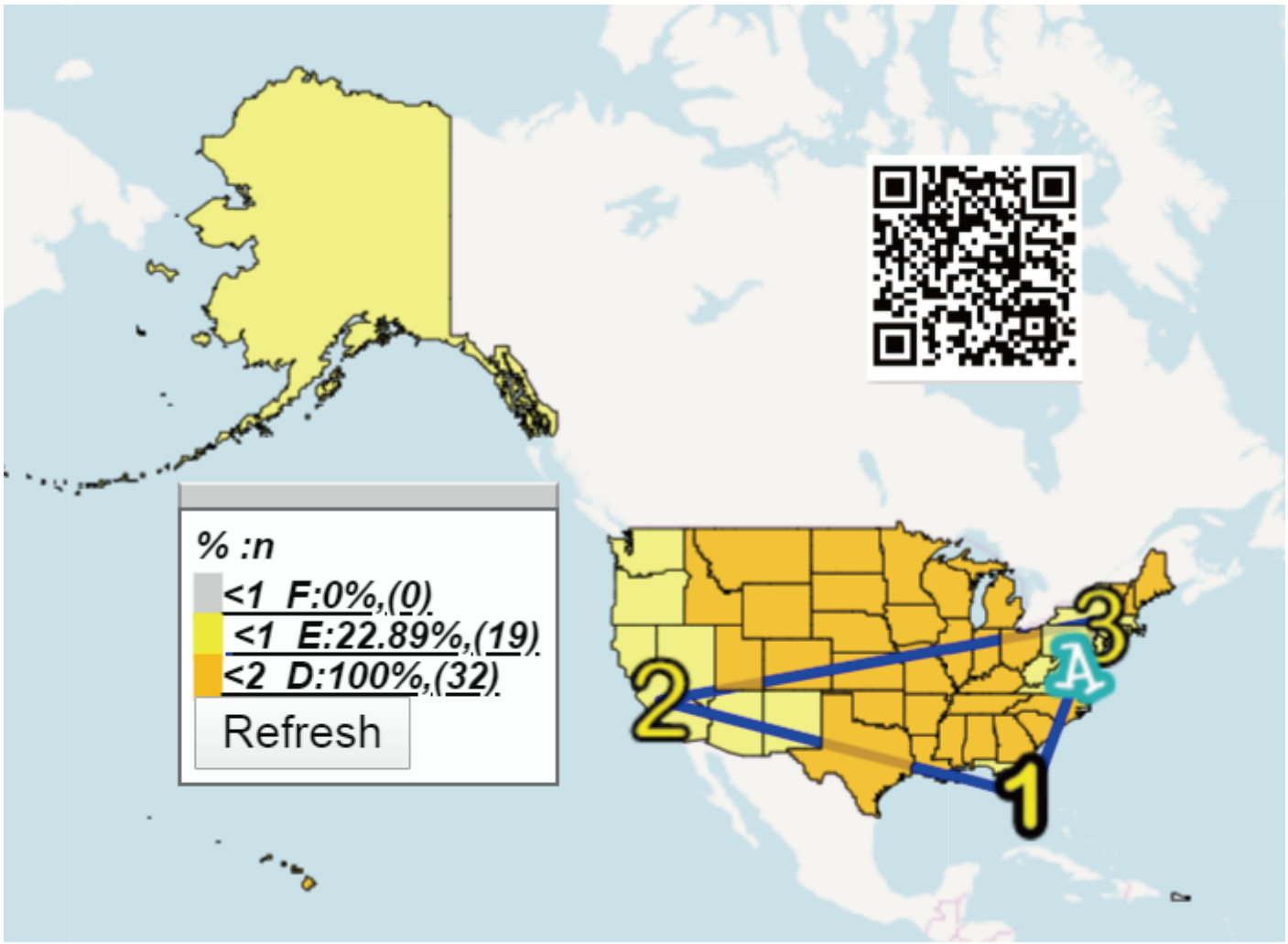

Figure 4

Two grades denoting the hospital-service quality for each state in the US(note. the symbol A denotes the location of Washington DC and the darker hsve higher grades)

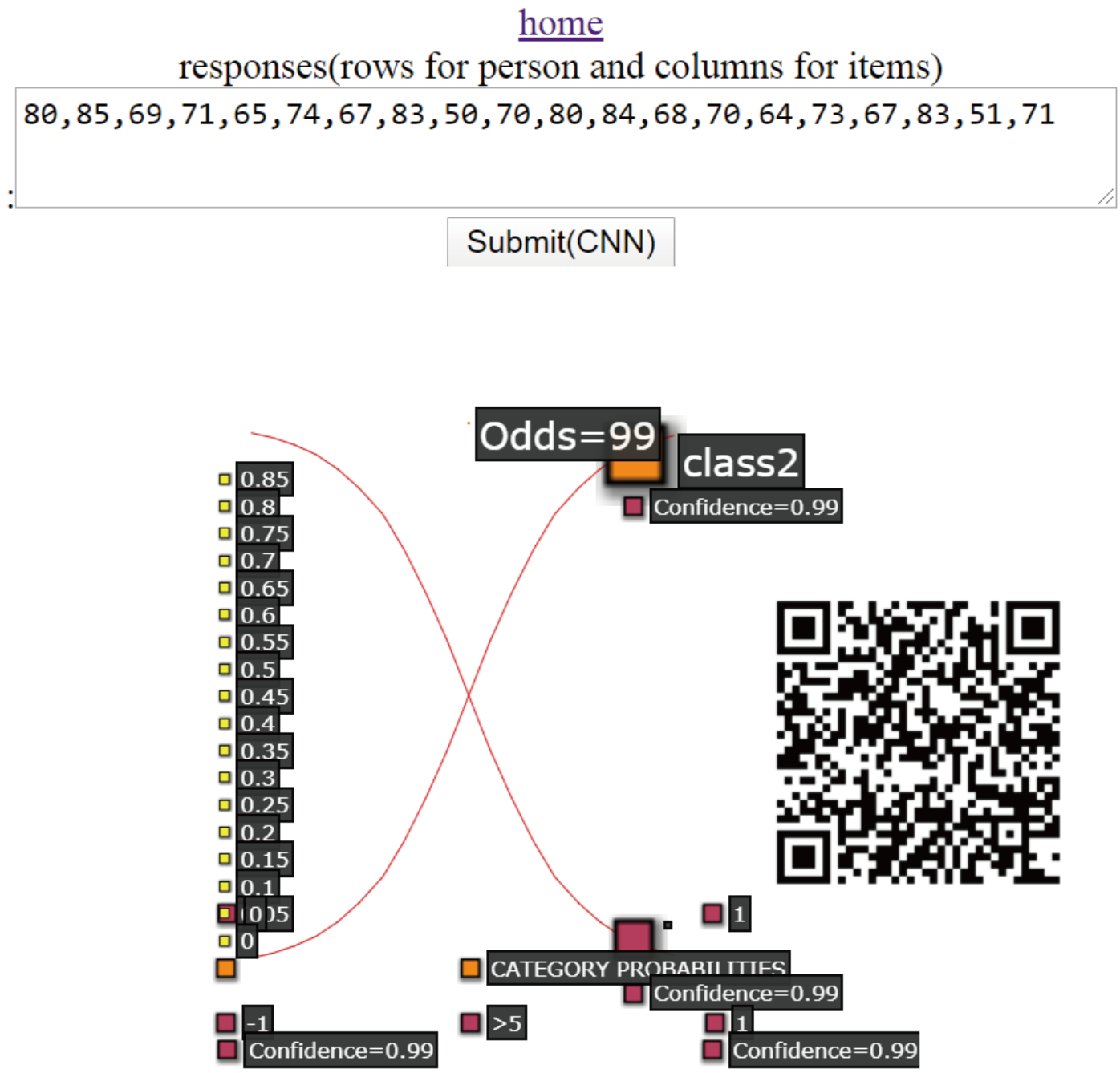

Figure 5

The snapshot of an app for classifying the grade of hospital service quality on a smartphone

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- dataset.xlsx

- Add5forCNNinterpretation.docx
- Additionalfile3.docx
- questions.pdf