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Implementation of Artificial Neural Network using Scaled Conjugate Gradient in ISO 9001:2015 Audit Findings Classification

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Abstract: ***Auditors of Quality Management System (QMS) face challenges in generating accurate audit reports due to some factors that can be attributed to technical competence, experience, time, auditee reaction, and other factors. Incorrect clauses cited in audit reports may result to loss of integrity of the auditor and the auditing procedure itself, hence, it is important that auditors should be careful in citing clauses of the standard to avoid chaos and complaints from auditees. To resolve this issue, this paper presents the implementation of Artificial Neural Network (ANN) using Scaled Conjugate Gradient (SCG) algorithm to classify audit findings based on the clauses of the ISO 9001:2015 QMS Requirements international standard. In this paper, the author explored how the neural network can predict the correct clause of the standard according to text patterns of audit findings. Based on modelling results, the neural network has generated a Cross Entropy (CE) values of 6.39, 18.09, 18.09 and Percentage Error (PE) values of 21.83, 21.58, and 22.39 in training, testing, and validation environments, respectively. Moreover, the model has achieved a combined Classification Accuracy (CA) of 96%, as for which, based on the actual implementation, the model has accurately predicted 95% of the audit findings analyzed.***

Index Terms**:** ***Artificial Neural Network, Scaled Conjugate Gradient, Text Classification, ISO 9001 Audit Findings***

I. INTRODUCTION

The ISO 9001:2015 Quality Management System (QMS) Requirements is the most popular standard published by the International Organization for Standardization (ISO) and is used as reference by organizations to attain international quality certification. It promotes the adoption of a QMS, which comprises of activities, policies and procedures wherein an organization is required to consistently provide quality products and services that meet applicable statutory, regulatory, customer, organization, and standard requirements [1]. The standard is composed of 10 major and ninety 90 minor clauses, as shown on Table 1, which are used as reference by auditors in writing audit reports.

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Table I: ISO 9001:2015 Major and Minor Clauses

Major Clause	*Title*	*Minor Clauses*
4.0	Context of the Organization	4.1, 4.2, 4.3, 4.4, 4.4.1, 4.4.2
5.0	Leadership	5.1, 5.1.1, 5.1.2, 5.2, 5.2.1, 5.2.2, 5.3
6.0	Planning	6.1, 6.1.1, 6.1.2, 6.2, 6.2.1, 6.2.2, 6.3
7.0	Resources	7.1, 7.1.1, 7.1.2, 7.1.3, 7.1.4, 7.1.5, 7.1.5.1, 7.1.5.2, 7.1.6, 7.2, 7.3, 7.4, 7.5, 7.5.1, 7.5.2, 7.5.3, 7.5.3.1, 7.5.3.2
8.0	Operation	8.1, 8.2, 8.2.1, 8.2.2, 8.2.3, 8.2.3.1, 8.2.3.2, 8.2.4, 8.3, 8.3.1, 8.3.2, 8.3.3, 8.3.4, 8.3.5, 8.3.6, 8.4, 8.4.1, 8.4.2, 8.4.3, 8.5, 8.5.1, 8.5.2, 8.5.3, 8.5.4, 8.5.5, 8.5.6, 8.6, 8.7, 8.7.1, 8.7.2
9.0	Performance Evaluation	9.1, 9.1.1, 9.1.2, 9.2, 9.2.1, 9.2.2, 9.3, 9.3.1, 9.3.2, 9.3.3
10.0	Improvement	10.1, 10.2, 10.2.1, 10.2.2, 10.3

The standard requires an organization to undergo mandatory internal and external audits. Internal audits are conducted in planned intervals by an organization toward self-declaration of conformity while external audits are conducted by third-party Certifying Bodies (CB) to evaluate the conformity of the QMS against an audit criteria [2]. In writing audit reports, auditors describe the nonconformity, then indicate the appropriate clause of the standard. Considering that there are total of ninety (90) clauses to look at, auditors may have hard time identifying the correct clause of the standard. This is practically true when a specific clause is applicable to multiple cases and when an auditor hurrily beats deadlines in writing audit reports. Incorrect clauses cited in an audit report results in a loss of integrity of the auditing procedure or the competence of the auditor concerned. Hence, auditors should be careful in citing clauses to avoid complaints from the auditees. One of the techniques explored in resolving similar cases is the use of text classification in supervised machine learning environment. Among the traditional algorithms used for this purpose are not limited to Naïve Bayes, Support Vector Machines, Discriminant Analysis, and Nearest Neighbors.

These algorithms, however, have imperfections in terms of generalization ability, data sparsity and dimension explosion. This is where Artificial Neural Networks (ANN) are preferred due to their capability to improve defects and feature extraction process, stronger learning ability and higher prediction accuracy [3]. Among the popular ANNs used in text classification purposes are not limited to feed-forward [4], cascaded [5], convolutional [6], recurrent [7], fuzzy neural [8], or combinations thereof [9]. While there is no perfect model that fits into any text classification application, there is still a gap on the extent of how a specific model can best predict an output depending on its intended purpose. Another popular algorithm used for supervised text classification application due to its documented technical capabilities is the Scaled Conjugate Gradient (SCG) [10]. SCG is a fast, fully-automated and robust optimization algorithm with modest memory requirements [11]. SCG is faster than Back Propagation (BP), Conjugate Gradient algorithm with Line Search (CGL), and Broyden-Fletcher-Goldfarb-Shanno-memoriless-quasi-Newton (BFGS). It is fast as the Levenberg-Marquadt (LM) on function approximation but it is actually faster than the latter in large networks. Moreover, SCG is at par with Resilient Backpropagation (RP) in terms of speed in resolving pattern recognition problems but it is more robust in terms of error reduction [12]. And lastly, SCG has been found to be very efficient in terms of training speed and accuracy particularly for text classification purposes [13, 14]. Despite the wide range of use-cases of SCG, it is interesting to note that this algorithm has not been utilized yet for ISO 9001 audit findings classification. This is manifested on the dearth of scientific publication related to the implementation of SCG for QMS. The motivation of this paper lies on proving the potential capabilities of SCG in resolving accuracy of ISO 9001:2015 audit reports, particularly in citing correct clauses of the standard based on text patterns of audit findings. For this purpose, the author explored the feasibility of using SCG as answer to the above-mentioned issues through simulation and practical implementation.

II. METHODOLOGY

With the use of MATLAB computing software, the author conducted this research by adhering to the machine learning (ML) workflow as illustrated on Fig. 1.

Fig. 1: ML Workflow

The author initially accessed a corpus repository with 5172 data set, composed of texts of the ISO 9001:2015 requirements and actual internal and external audit findings from the Technological University of the Philippines- an ISO 9001:2015 certified institution. Shown on Fig. 2 is a sample screenshot of the input corpus taken from the texts of clauses 4.0 to 10.3 of the standard while Fig. 3 shows a sample screenshot of audit findings generated from online Corrective Action Reports (CAR) logs.

Clause	Requirements
8.1	Operational planning and control The organization shall plan, implement and control the processes (see 4.4) n
8.2	Requirements for products and services
8.2.1	Customer communication Communication with customers shall include: a) providing information relating t
8.2.2	Determining the requirements for products and services When determining the requirements for the products a
8.2.3	Review of the requirements for products and services
8.2.3.1	The organization shall ensure that it has the ability to meet the requirements for products and services to be off
8.2.3.2	The organization shall retain documented information, as applicable: a) on the results of the review; b) on any
8.2.4	Changes to requirements for products and services The organization shall ensure that relevant documented in
8.3	Design and development of products and services
8.3.1	General The organization shall establish, implement and maintain a design and development process that is ap
8.3.2	8.3.2 Design and development planning In determining the stages and controls for design and development, th
8.3.3	8.3.3 Design and development inputs The organization shall determine the requirements essential for the :
8.3.4	8.3.4 Design and development controls The organization shall apply controls to the design and development p
8.3.5	Design and development outputs The organization shall ensure that design and development outputs: a) meet
8.3.6	Design and development changes The organization shall identify, review and control changes made during, or

Fig. 2: ISO 9001:2015 Requirements Corpus

Clause	Findings
7.5.1	In compliance to the Generally Accepted Accounting Principles (GAAP), the Government Accounting Standards Bo
7.5.3.1	QMS requires that documented information shall be controlled to ensure it is available and suitable for use, where a
8.1	The organization shall plan, implement and control the processes needed to meet the requirement and to implemen
8.5.2	In conformity to the standard, the organization shall control the unique identification of the outputs when traceability
9.1.3	According to the standards, the organization shall analyse and evaluate appropriate data and information arising fr
7.2	According to the standard, the organization shall where applicable, take actions to acquire the necessary competen
8.5.1	The standard requires that the organization shall implement production and service provision under controlled cond
4.4	The organization shall determine the processes needed for the QMS and their application throughout the organizat
6.2	No Action plan to achieve quality objectives when they are not met
7.2	There was no documented information available during that time of visit for validation.
7.4	Information is cascaded or communicated verbally.
7.3	Upon validation from the QA office, the documented issues were submitted by the process office.
6.2.1	The Quality objectives shall be monitored. When asked about their monitoring system in terms of detailed office tar
9.2.2	No QMS internal audit results for Q3 FY 2018
8.1	No 5s technical audit results for Q3 FY 2018
7.5.1	There is an existing subsystem that provides details of information to final books of entry, thus establishing audit tra
7.5.3.1	There is an existing subsidiary ledger for payables and receivables however due to hectic schedule of some staff in
8.1	The reconciliation procedures are in placed in the accounting office however some reconciliations are not immediat
8.5.2	Proper accounting for Construction in Progress exists, however due to lack of electricity and water submeters for ea
9.1.3	Was not able to obtain and retain ledgers and documented information from the business center for consignment s
7.2	Lapsing schedules on fixed assets are maintained however reconciliation with the supply office is less frequently do
8.5.1	Non-existence of documents pertaining to prior years.
4.4	Summary list of cash advances and subsidiary ledgers by accountable officers are being maintained and updated t
9.1.2	No CSF Data as of October 6, 2017

Fig. 3: Internal and External Audit Findings Corpus

Afterwards, the author then classified the audit findings and standard requirements as input corpus, while the equivalent standard clauses as target corpus. The input corpuses were then preprocessed by transforming all texts to lowercase and parsing less helpful artifacts such as common words, punctuations, html, and URLs. The author utilized stop-words, lexicon, and regexp tokenization techniques in order to enhance the preprocessing method. The author then utilized the Bag-of-Words (BOW) model of text mining to extract the reliable features of the input corpuses through count term frequency, Inverse Document Frequency (IDF), and L2 Euclidean regularization techniques. Here, the BOW model was set to have a vocabulary of known words and parameters to measure the presence of known words also known as tokens. Depicted on Fig. 4 is a sample screenshot of the tokenization of input corpuses, which numerical equivalents were generated as input vectors. At this phase, the target corpus was also then transformed to numerical target vectors in order to be understood by the network for further modelling purposes.

```
>> documents = tokenizedDocument(textDataTrain);
>> documents

documents =

  775×1 tokenizedDocument:

     51 tokens: In compliance to the Generally Accepted Accounting Principles ( GAAP ) , the Governme
     39 tokens: QMS requires that documented information shall be controlled to ensure it is availabl
    128 tokens: The organization shall plan , implement and control the processes needed to meet the
     62 tokens: In conformity to the standard , the organization shall control the unique identificat
     79 tokens: According to the standards , the organization shall analyse and evaluate appropriate
     77 tokens: According to the standard , the organization shall where applicable , take actions to
    132 tokens: The standard requires that the organization shall implement production and service pr
     14 tokens: There was no documented information available during that time of visit for validatio
      7 tokens: Information is cascaded or communicated verbally .
     17 tokens: Upon validation from the QA office , the documented issues were submitted by the proc
     42 tokens: The Quality objectives shall be monitored . When asked about their monitoring system
      9 tokens: No QMS internal audit results for Q3 FY 2018
      9 tokens: No 5s technical audit results for Q3 FY 2018
     17 tokens: Total Score is 21 ( Opportunity for Improvement ) per 5S Audit checklist transaction
     37 tokens: There is an existing subsystem that provides details of information to final books of
     47 tokens: The reconciliation procedures are in placed in the accounting office however some rec
```

Fig. 4. Input Tokens

After tokenization of input vectors and transformation of target vectors, the author then modeled a standard two-layer, feed-forward backpropagation ANN, as shown on Fig. 5. Using MATLAB computing software, the input and output layers of the model were designed with a sigmoid transfer function and a SoftMax transfer function, respectively.

The model consisted of 5172 input vectors (X_{5172}) composed of tokenized ISO 9001 requirements and audit findings; two (2) set of hidden layers composed of 10 neurons each; and 90 target vectors (Y_{90}) made of the categorized clauses of the standard. To train the network in a supervised learning environment, the author implemented the SCG algorithm. Considering reliability requirements of the model, the author set the training, validation, and testing data to 70%, 15%, and 15%, respectively. The intent of the validation was to ensure that network generalization stops training before overfitting while testing was conducted to ensure that network generalization was completely independent from training results. Furthermore, the model was set to stop automatically when generalization stops improving as indicated by any increase of cross-entropy error values of the validation data.

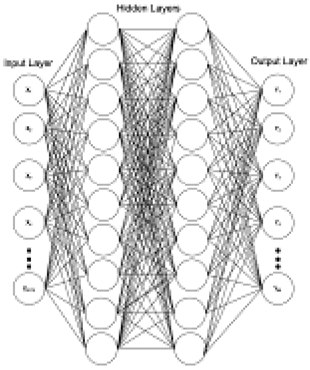

Fig. 5: ANN Model with 5172 Standard Requirements and Audit Findings (Input Vectors) and 90 Standard Clauses (Target Vectors)

Afterwards, the author iterated the model in order to fine tune its desired output and get the lowest possible prediction errors. While the results of iterations were randomly generated by the algorithm, the author run the training for at least 10 trials using a computer with Intel Core i5 2.5 GHz processor with 8 GB 1600 MHz DDR3 memory specifications. The results of training, testing and validation were then evaluated using Cross Entropy (CE) and Percentage Error (PE) parameters. Minimized CE values result in good classification, which means that the lower the CE values the better. Meanwhile, PE indicates the fraction of misclassified samples where in 0 means no misclassification while 100 means maximum misclassification performance. This also means that the lower the PE values, the better. Afterwards, the author evaluated the Classification Accuracy (CA) of the model based on its actual implementation on sample audit findings. Specifically, the following formulas were used by the author to determine the CE (1), PE (2), and CA (3) of the model, respectively:

$$CE = -\sum_{c=1}^{N} yo, c \log (po, c) \qquad (1)$$

"CE" is the Cross Entropy value; "N" is the total number of classes; "log" is the natural log value; "y" is the binary indicator of 0 or 1 where class label "c" is the correct classification of observation "o"; and "p" is the predicted probability observation "o" of class "c".

$$PE = \frac{100}{n}\sum_{t=1}^{n}\left[At\text{-}\frac{Pt}{At}\right], x\ 100 \qquad (2)$$

"At" is the actual value and "Pt" is the predicted value. The absolute value is summed for every predicted point in time "t" and divided by the number of fitted points "n".

$$CA = NC / TP \qquad (3)$$

"CA" is the Classification Accuracy; "NC" is the number of correct predictions; and "TP" total number of predictions.

After the modelling, the author then implemented the ANN to an actual set of 20 audit findings. Here, the prediction accuracy of the application was determined by using the same CA formula (3).

III. RESULTS AND DISCUSSION

The following Fig. 6 shows the results Bag-of-Words Model. In each audit finding text, the words were stemmed to generate reliable features. Here, the known words or tokens were coded to score their equivalent numerical values. As a result, the model was able to recognize 5172 total document count and 3262 total tokens. Fig. 7 and 8, on the other hand, illustrate the sample screenshots on the transformation of both input and output corpuses into input and target vectors, which were used by the model during training.

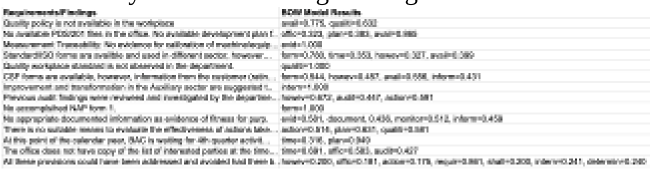

Fig. 6: Sample BOW Model Results

	1	2	3	4	5	6	7	8	9	10
1	1	1	1	0	0	0	0	0	0	2
2	0	2	5	4	3	9	5	3	2	0
3	0	2	7	2	0	6	0	0	1	2
4	0	12	0	5	0	8	0	0	4	5
5	0	0	0	0	0	1	1	0	0	0
6	0	4	16	3	0	15	0	0	2	3
7	0	0	4	1	0	0	1	0	0	1
8	0	0	0	0	0	0	0	0	0	0
9	1	0	0	0	0	1	0	0	0	0
10	0	9	22	0	0	7	1	1	0	1
11	0	1	3	0	0	8	0	0	0	1
12	0	0	0	0	0	0	0	0	0	0
13	0	2	0	1	0	3	1	1	0	1
14	0	0	2	1	0	2	0	0	1	1
15	0	4	13	0	0	6	0	0	0	0
16	0	0	0	0	0	1	0	0	0	0
17	0	0	6	1	0	3	1	0	0	1
18	0	3	9	1	0	6	2	0	1	2
19	0	0	0	0	0	1	0	0	0	0

Fig. 7: 5172x3262 Double Input Vectors

	1	2	3	4	5	6	7	8	9	10
1	1	1	1	0	1	1	0	0	0	1
2	0	0	0	1	0	0	1	1	1	0
3	1	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0
7	1	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0
9	1	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0
11	1	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0
13	1	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0
15	1	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0
17	1	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0
19	1	0	0	0	0	0	0	0	0	0

Fig. 8. 90x3262 Double Target Vectors

Meanwhile, the results of performance evaluation of the model are shown on the following figures and tables. With total of 5172 input vectors and 90 target vectors, the ANN was trained using SCG algorithm in order to get the best possible prediction performance.

Summarized on Table 2 is the performance of the network in three types of environments. From the 5172 input vectors, only a total of 3262 tokens were considered for the actual training. 2284 (70%) of the tokens were used for training, while 489 (15%) were used for validation and another 489 (15%) for testing purposes. After ten iterations, the best possible CE values generated were recorded at 6.39, 18.09, 18.09 while PE values were 21.83, 21.58, and 22.39 in training, validation, and testing environments respectively.

Table II: ANN Model Performance Results

Environment	Samples	CE	PE
Training	2284	6.39	21.83
Validation	489	18.09	21.58
Testing	489	18.09	22.39

Meanwhile, summarized on Table 3 is the progress results of the ANN. On its best performance state, the network stopped training at maximum epoch of 74 iterations with maximum training time of 6 seconds; it has minimized its performance rate of 0.00432 against the goal; fallen below performance gradient rate of 0.00455; and has reached maximum 6 validation checks.

Table III: ANN Model Best Performance Progress Results

Parameters	Values
Epoch Time	74 Iterations
Time	6 Seconds
Performance	0.00432
Gradient	0.00455
Validation Checks	6

Illustrated further on Fig. 9 is the best validation performance plot of the network in terms of ratio of CE and epoch in training, testing, and validation samples. As shown, the network generated the lowest validation error of 0.0036495 at epoch 68.

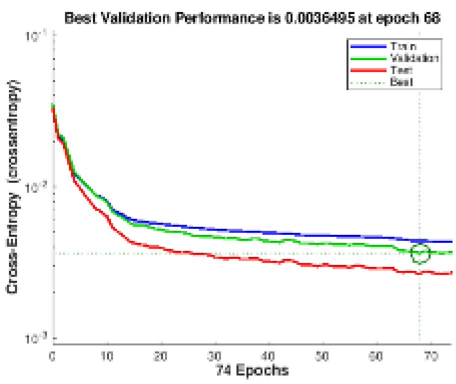

Fig. 9. Best Validation Performance Results

Moreover, Fig. 10 shows the best performance of the network in validation state where it generated a gradient rate of 0.0045521at epoch 74 while Fig. 11 illustrates the error histogram of the network with 20 bins.

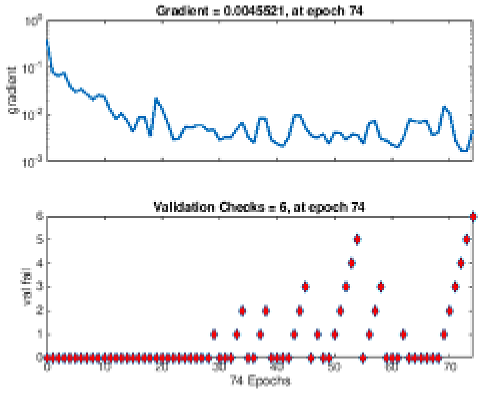

Fig. 10: Training State Results

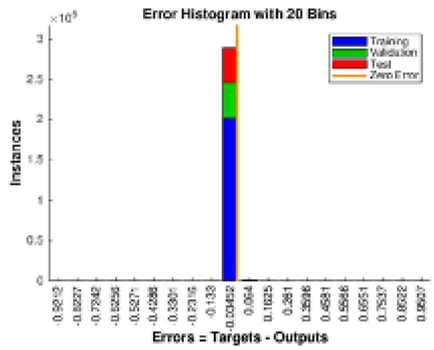

Fig. 11: Histogram Results

The next Fig. 12, 13, 14 and 15 show the confusion matrices for training, testing, validation, and overall data combined, respectively. With the output vectors clustered (major clauses from 4.0 to 10.3 or total of 7 clustered outputs), the network outputs were found to be accurate. As shown, the network has Classification Accuracy (CA) of 95.1%, 94.7%, 97.2%, and 96% in training, testing, validation and overall performance, respectively.

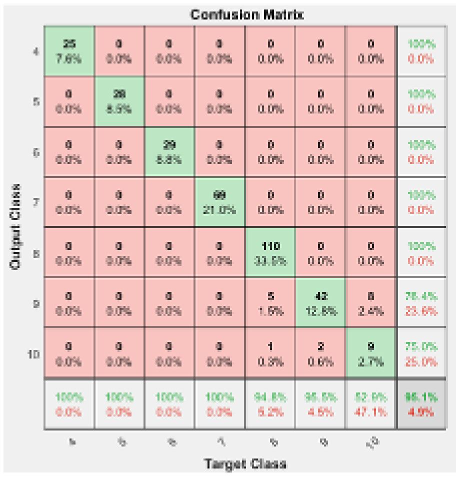

Fig. 12: Classification Accuracy of Training Data

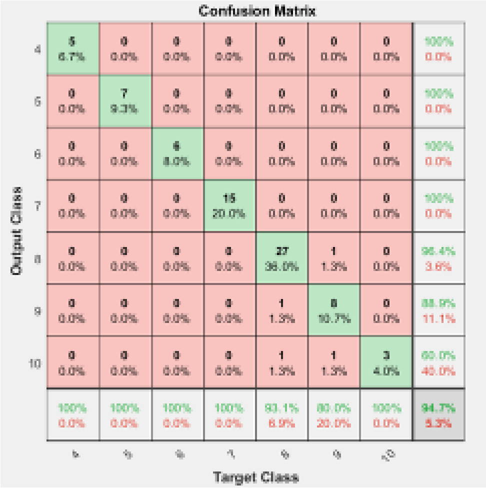

Fig. 13: Classification Accuracy of Testing Data

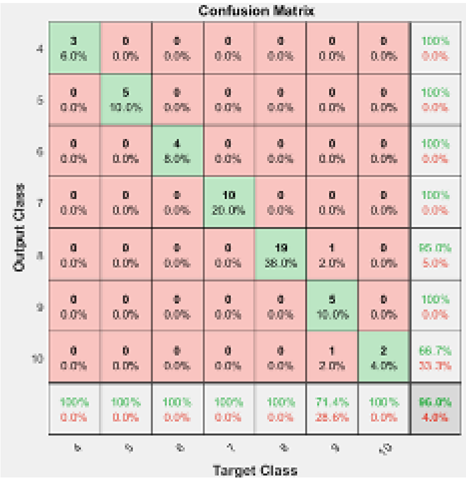

Fig. 14: Classification Accuracy of Validation Data

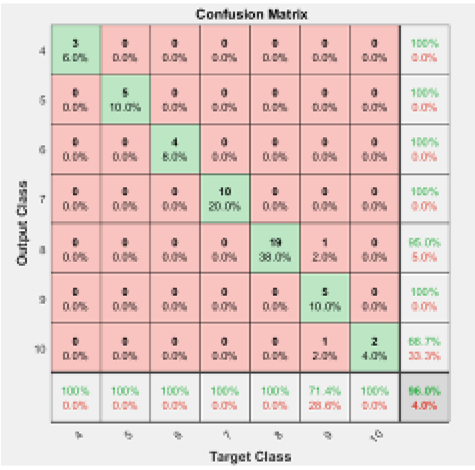

Fig. 15: Overall Classification Accuracy of the Model

Illustrated on Fig. 16 is the Receiver Operating Characteristics (ROC) plot of the model. The plot depicts the relationship between true positive rate or sensitivity versus the false positive rate or 1 – specificity while the threshold of the network is varied. The value of 1 on the ROC plot indicates the most perfect relationship where sensitivity and specificity are measured at 100% levels. The ROC plot reveals that the validation data has higher sensitivity and specificity values as compared with testing and training data. This is manifested on the curves leaning toward the upper left corner of the curve where blue aligns closer to 1 than red and green plots. The overall ROC plot proves that the model performs best in validation, followed by training, then in testing environments.

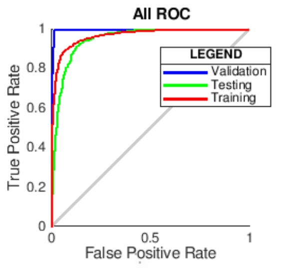

Fig. 16. ROC Plot Results

After the modelling, the ANN was implemented using programming scripts for practical application. The following Fig. 17 shows a screenshot of the actual implementation of the ANN in predicting the correct clause of the ISO 9001:2015 standard based on sample audit findings. The results are summarized on Table 4 where in based on 20 actual audit findings sampled, the ANN was able to predict 19 correctly, or a percentage prediction accuracy of 95%.

```
>> str = [ ...
    "No CSF or customer satisfaction result."
    "Incomplete Data on IPR."
    "Current SPMS needs to be calibrated with the quality objectives requirements of the QMS."
    "The work instructions manual is not available at the time of audit."
    "There is a need to review the relevance of the office functional chart."];
documentsNew = tokenizedDocument(str);
XNew = encode(bag,documentsNew);
labelsNew = predict(mdl,XNew)

labelsNew = 

  5×1 categorical array

     9.1.2
     4.2
     6.2.1
     7.5.3.2
     5.3
```

```
>> str = [ ...
    "No Electrical maintenance plan"
    "Office should implement 5S to improve cleanliness"
    "No accomplished NAP form 1."
    "Procurement and BAC should be merged to improve process."
    "No IEI"];
documentsNew = tokenizedDocument(str);
XNew = encode(bag,documentsNew);
labelsNew = predict(mdl,XNew)

labelsNew = 

  5×1 categorical array

     7.1.4
     8.1
     7.5.3
     8.1
     4.1
```

Fig. 17. Sample Screenshots of Actual Prediction Results

Table IV: ANN Model Actual Prediction Results

Trial	Audit findings	Predicted Clause	Actual Clause
1	There is no suitable means to evaluate the effectiveness of actions to address risks and opportunities.	9.1.3	9.1.3
2	No QMS internal and external audit results for Q3 FY 2018	9.2.2	9.2.2
3	No interested parties identified	4.2	4.2
4	There is no list of internal and external issues assessment form at the time of audit	4.1	4.1
5	No action plan to achieve quality objectives when they are not met	6.2	6.2
6	No electrical maintenance plan	7.1.4*	7.1.5
7	Office should implement 5s to improve cleanliness	8.1	8.1
8	No accomplished NAP Form 1.	7.5.3	7.5.3
9	Procurement and BAC should be merged to improve process.	8.1	8.1
10	No IEI.	4.1	4.1
11	There is a need for standardized wall markings where vision, mission, and quality policy statements are shown	7.1.3	7.1.3
12	Pending Audit Result	9.2.2	9.2.2
13	No IPR	4.2	4.2
14	During the time of Audit, there is no available ISO format of Admission Form.	7.5.1	7.5.1
15	Non-existence of documents pertaining to prior years.	8.5.1	8.5.1
16	No CSF or customer satisfaction result.	9.1.2	9.1.2
17	Incomplete Data on IPR.	4.2	4.2
18	Current SPMS needs to be calibrated with the quality objectives requirements of the QMS.	6.2.1	6.2.1
19	The work instructions manual is not available at the time of audit.	7.5.3.2	7.5.3.2
20	There is a need to review the relevance of the office functional chart.	5.3	5.3
Number of Correct Predictions:			**19**
Total Number of Predictions made:			**20**
% Prediction Accuracy:			**95**

IV. CONCLUSION

This research was conducted to propose a potential solution in resolving common challenge of citing ISO 9001:2015 clauses in audit findings. To do this, the author designed a two-layer feed-forward backpropagation Artificial Neural Network (ANN) with sigmoid and SoftMax transfer functions that can classify 5172 text patterns of audit findings and can predict 90 standard clauses. After preprocessing and tokenization of input vectors, through Bag-of-Words method, and transformation of target vectors, the ANN model was eventually trained using SCG algorithm where 70%, 15%, and 15% of the 3262 tokens for were used for training, validation, and testing environments, respectively. After ten iterations, the network generated the best Cross Entropy (CE) values of 6.39, 18.09, 18.09 and Percentage Error (PE) values of 21.83, 21.58, and 22.39 in training, validation, and testing environments respectively. Moreover, the Classification Accuracy (CA) of the model was evaluated at 95.1%, 97.2%, 94.7%, and 96% in training, testing, validation and overall performance respectively. Lastly, the ANN model was implemented in actual audit findings in order to prove its performance. Based on evaluation results of the sample audit findings, the model was able to predict 19 out of 20 clauses correctly or total of 95% prediction accuracy. As such, the model, particularly the use of SCG algorithm, has been proven to be efficient and effective in classifying text patterns of ISO 9001:2015 audit findings. Future works are recommended to focus on adding more audit findings from other institutions to improve variability and classification performance. It is also better to compare SCG with other classification algorithm to explore other alternatives for optimal outcomes.

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