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Supriya Kapoor *Editors*

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DAFTAR ISI

Contents

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Sebastiano Battiato is a full professor of Computer Science at the University of Catania. He received his degree in Computer Science (summa cum laude) in 1995 from the University of Catania and his Ph.D. in Computer Science and Applied Mathematics from the University of Naples in 1999. From 1999 to 2003 he was the leader of the “Imaging” team at STMicroelectronics in Catania. He joined the Department of Mathematics and Computer Science at the University of Catania in 2004 (respectively as assistant professor, associate professor in 2011 and full professor in 2016). He has been Chairman of the Undergraduate Program in Computer Science (2012-2017), and Rector's delegate for Education: postgraduates and Phd (2013-2016). He is currently the Scientific Coordinator of the PhD Program in Computer Science at the University of Catania. He is involved in research and directorship of the IPLab research lab (http://iplab.dmi.unict.it). He coordinates IPLab’s participation on large scale projects funded by national and international funding bodies, as well as by private companies. Prof. Battiato has participated as principal investigator in many international and national research projects. His research interests include Computer Vision, Imaging technology and Multimedia Forensics. He has edited 6 books and co-authored about 200 papers in international journals, conference proceedings and book chapters and has also been a guest editor of several special issues published in International Journals. He is also co-inventor of 22 international patents, reviewer for several international journals, and has been a regular member of numerous international conference committees.

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Dr. Wenbing Zhao is a Professor of Electrical and Computer Engineering at Cleveland State University, Cleveland, Ohio, USA. Dr. Zhao has done research in a number of different areas, including fault tolerance computing, computer and network security, smart and connected healthcare, machine learning and control, quantum optics and superconducting physics. Currently, his research focuses on dependable distributed computing, and smart and connected healthcare. He is also exploring an exciting emerging research area on medical cyber physical systems, where he could integrate dependable computing with smart and connected healthcare. Dr. Zhao's recent research has been funded by the National Science Foundation (CNS-0821319), US Department of Transportation (via CSU Transportation Center), and Cleveland State University (several FRD grants and a Faculty Scholarship Initiative grant). Dr. Zhao has authored a research monograph, titled "Building Dependable Distributed Systems," and contributed 22 book chapters and over 100 peer-reviewed journal and conference publications. He also has a US patent on consistent time service for fault tolerant distributed systems and another patent pending on privacy-aware human motion tracking. Dr. Zhao has been very active in professional services. Other than the Departmental/College/University duties, he has served on several NSF panels, and on the organizing and technical program committees of numerous conferences/workshops. Dr. Zhao is a senior member of Institute of Electrical and Electronics Engineers (IEEE). He is currently serving as a member of the executive board of the IEEE Cleveland Chapter.

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Dr Chen is Professor of Data Analytics, Research Director for School of Computing at Ulster University, UK. His current research interests include data analytics, pervasive computing, artificial intelligence, user-centred intelligent systems and their applications in smart healthcare. Dr Chen is an IET Fellow, an IEEE Senior Member, a co-founder and co-director of the IEEE CIS" User-centred Smart Systems" Task Force. He is currently the co-investigator of the British Telecommunication Ireland Innovation Centre, and was the coordinator of the EU Horizon2020 MSCA ITN ACROSSING project and has serves as the principal investigator for the EU AAL PIA project, the MobileSage project and FP7 MICHELANGELO project, and a number of projects funded by industry and third countries. Dr Chen has over 230 publications in internationally recognised journals, book series and conferences. He is the general chair or program chair for IEEE Smart World Congress 2019, IEEE UIC2017, IEEE HealthCom2017, SAI Computing 2017, IEEE UIC2016, IntelliSys2016, MoMM2015/2014, SAI2015, IWAAL2014, UCAMI2013, and an organising chair of many workshops. He is an associate editor of IEEE THMS, and guest editors for IEEE Computer and THMS, Elsevier PMC and IJDSN and Springer PUC and AIHC. He has delivered nearly 30 talks, keynotes and seminars in various forums, conferences, industry and academic events. Luke has served as an expert for research funding assessment for UKRI, EU Horizon2020, Canada, Chile, Netherlands and Denmark.

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Professor David Stupples specialises in research and development of networked electronic and radio systems. For a number of years he undertook research in military surveillance systems at the Royal Signal and Radar Establishment at Malvern in the UK, followed by satellite surveillance and systems research for the UK Government. He then spent three years developing secure communications and signals processing for surveillance satellites and air defence systems for Hughes Aircraft Corporation in the US. In his early career, Dr David Stupples was employed in radar and communications systems development by the Royal Air Force. Later, he was a senior partner with PA Consulting Group where he was responsible for the company's consultancy work on the design, build and operation large-scale surveillance networks for world-wide clients. His current research is in networked systems with a focus on multi-sensor surveillance using both active and passive sensors. This research work has intelligence, military and commercial uses with the latter applying to future air traffic management. The research employs a variety of systems modelling techniques particularly to assess the behaviour of networked systems under stressed conditions in order to identify and assess emergent properties for their impact on both safety and integrity. Professor David Stupples has been applying this research to internet security, particularly focused on cyber terrorism and organised cyber crime for both the UK government and commercial companies. This work has required the development of new systems analysis and modelling techniques to understand the behaviour of complex internet systems. However, he still maintains an active interest in radar systems research; particularly synthetic aperture systems.

Yaxin Bi

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Yaxin Bi is a Reader in School of Computing and Mathematics at University of Ulster. His research interests are multiple classification systems and ensemble learning, the Dempster-Shafer theory of evidence, big data analytics for satellite data exploitation, data/text mining for sentiment and media content analyses, and sensor fusion for understanding human behaviours in applications of Smart Homes. He has been involved in a number of European Frameworks projects since 1997 and has more than 100 peer-reviewed publications in international journals and conferences, including journals of Artificial Intelligence, IEEE Transactions of Knowledge and Data Engineering and International Journal of Approximate Reasoning. He was a program co-chair of the 4th International Conference on Knowledge Science, Engineering and management (KSEM) 2010 and a steering committee member of KSEM and SAI.

Chaomin Luo

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Chaomin Luo (Senior Member, IEEE) received the Ph.D. degree in electrical and computer engineering from the University of Waterloo, Waterloo, ON, Canada, the M.Sc. degree in engineering systems and computing from the University of Guelph, Guelph, ON, Canada, and the B.Eng. degree in electrical engineering from Southeast University, Nanjing, China. His research interests include robotics and autonomous systems, machine learning, and intelligent systems. Dr. Luo was the recipient of the Best Paper Awards in IEEE International Conference on Information and Automation, International Conference on Swarm Intelligence, and SWORD Conference. He is currently an Associate Editor for the International Journal of Robotics and Automation, International Journal of Swarm Intelligence Research and IEEE Transactions on Cognitive and Developmental Systems. He was an Associate Editor for 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems, and a Tutorials Co-Chair in 2020 IEEE Symposium Series on Computational Intelligence (IEEE-SSCI). He is currently an Associate Professor with the Department of Electrical and Computer Engineering, Mississippi State University, Mississippi State, MS, USA. Dr. Luo is active nationally and internationally in his research field. He was the panelist in 2017 NSF GRFP Panelist program. He was the Program Co-Chair in 2018 IEEE International Conference on Information and Automation (IEEE-ICIA'2018). He was the Plenary Session Co-Chair in the 2019 and 2018 International Conference on Swarm Intelligence, and he was the Invited Session Co-Chair in the 2017 International Conference on Swarm Intelligence. He was the General Co-Chair of the 1st IEEE International Workshop on Computational Intelligence in Smart Technologies (IEEE-CIST 2015), and Journal Special Issues Chair, IEEE 2016 International Conference on Smart Technologies (IEEE-SmarTech), Cleveland, OH, USA. Also, he was Chair and Vice Chair of IEEE SEM - Computational Intelligence Chapter and was a Chair of IEEE SEM - Computational Intelligence Chapter and Chair of Education Committee of IEEE SEM.

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Supriya Kapoor oversees all conference management activities for the organization including but not limited public and corporate relations, messaging, on-going communications, media outreach and material development. Supriya is happy to work for an organization that changes the world through global interaction and wisdom sharing. She has a breadth of experience in prospecting, relations, training, presentations, publication and financial planning. Supriya has built extensive networks that bring professional growth to the conferences. Before directing herself to management role, Supriya was a subject matter expert in the area of database and backend technologies.

Advances in Intelligent Systems and Computing

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Intelligent Systems and Applications

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Editor's Preface

The Intelligent Systems Conference (IntelliSys) 2019 was held on September 5 and 6, 2019, in London, UK. The Intelligent Systems Conference is a prestigious annual conference on areas of intelligent systems and artificial intelligence and their applications to the real world, which is built on the success of the IntelliSys conferences in the past five years held at London.

This conference not only presented the state-of-the-art methods and valuable experience from researchers in the related research areas, but also provided the audience with a vision of further development in the fields. The research that comes out of a series of the IntelliSys conferences will provide insights into the complex intelligent systems and pave a way for the future development.

The Program Committee of IntelliSys 2019 represented 25 countries, and the authors submitted 546 papers from 45 countries. This certainly attests to the widespread international importance of the theme of the conference. Each paper was reviewed on the basis of originality, novelty and rigorousness. After the reviews, 223 were accepted for presentation, out of which 189 papers are finally being published in the proceedings.

The event was a two-day program comprised of 24 paper presentation sessions and poster presentations. The themes of the contributions and scientific sessions ranged from theories to applications, reflecting a wide spectrum of artificial intelligence. We are very gratified to have an exciting lineup of featured speakers who are among the leaders in changing the landscape of artificial intelligence and its application areas. Plenary speakers include: Grega Milcinski (CEO, Sinergise), Detlef D Nauck (Chief Research Scientist for Data Science at BT Technology), Giulio Sandini (Director of Research - Italian Institute of Technology) and Iain Brown (Head of Data Science, SAS UK&I).

The conference would truly not function without the contributions and support received from authors, participants, keynote speakers, program committee members, session chairs, organizing committee members, steering committee members and others in their various roles. Their valuable support, suggestions, dedicated commitment and hard work have made the IntelliSys 2019 successful.

It has been a great honor to serve as the general chair for the IntelliSys 2019 and to work with the conference team. We believe this event will certainly help further disseminate new ideas and inspire more international collaborations.

Kind Regards,
Yaxin Bi
Conference Chair

ARTIKEL

Determining the Number of Hidden Layers in Neural Network by Using Principal Component Analysis

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Abstract. One of the challenges faced in the success of Deep Neural Network (DNN) implementation is setting the values for various hyper-parameters, one of which is network topology that is closely related to the number of hidden layers and neurons. Determining the number of hidden layers and neurons is very important and influential in DNN learning performance. However, up to now, there has been no guidance on it. Determining these two numbers manually (usually through trial and error methods) to find fairly optimal arrangement is a time-consuming process. In this study, we propose the method used for determining the number of hidden layers was through the number of components formed on the principal component analysis (PCA). By using Forest Type Mapping Data Set, based on PCA analysis, it was found out that the number of hidden layers that provide the best accuracy was three. This is in accordance with the number of components formed in the principal component analysis which gave a cumulative variance of around 70%.

Keywords: Neural network · Hidden layer · PCA

1 Introduction

Neural network has been successfully applied in various fields such as computer science, finance, medicine, engineering, physics, and so forth. The main reason is that neural network could approach arbitrary function. Over the past 30 years, a number of researches showed that artificial neural network called as feedforward network with one hidden layer can approach all functions arbitrarily [1–6]. One of important aspects for designing neural network is architecture or its topology that is closely related to the capability of generalization [7, 8]. Since the era of deep learning, the use of neural network that has more than one hidden layer is a research topic that caught researchers' interest. One of the challenges in the success of deep neural network implementation is setting values for various hyper-parameters, one of which is network topology that is closely related to the number of hidden layers and neurons. Determining the number of hidden layers and neurons is very important and influential in the performance of deep neural network [7, 8]. Therefore research to determine both of them is very necessary.

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According to some literatures aforementioned, determining the number of hidden layers or optimal number of neurons still has no clear guideline. Moreover, the roles and functions of both are explained minimally. Some literatures propose methods or ways to determine the number of hidden layers or neurons, but they are not generally applied due to the type of input and output data [9, 10]. Studies in this area still leave difficult research tasks [11]. Some of the methods mentioned are apparently not applicable for different types of data. The earlier researchers determined the number of hidden layers or neurons based on their experience. However, less experienced researchers even did it based on 'trial and error'. One of the methods that can be applied practically is through data mining techniques, clustering and regression [12–14]. In this study, the researcher did not explain the relationship between the number of clusters formed by feature extraction that is going to be used in machine learning process.

Although it is a difficult area of research, determining the number of hidden layers and neurons should be carried out. This is because they greatly determine the deep neural network learning performance. As a first step, a method or technique is needed to determine the number of hidden layers. Hidden layers in the neural network in stages represent increasingly complex features, while the main components of the PCA represent the information content that exists. By assuming that the complexity of features is in line with the size of the feature information, then in this study we propose a method specifically for determining the number of hidden layers in a neural network based on the number of main components formed on principal component analysis (PCA).

2 Related Work

Studies compared the use of one or two hidden layers focused on univariate and multivariate functions [4–6, 15]. Thomas [4, 5] got different result that the use of two hidden layers applied to predictive functions showed better performance. Guliyev and Ismailov [6] concluded that the use of one hidden layer was less capable of approaching the multivariate function, so the use of two hidden layers showed better performance.

To determine the number of hidden layers and neurons at once, the method is divided into two: automatically and manually [15]. Automatic determination uses models, but it also can be done without models. Manual determination uses certain formulas, some are done by trial and error. Automatic determination without a model consists of grid search (GS) and random search (RS). GS is generally used to optimize DNN parameters only if the number is very low. First, users choose a range of values to explore. Then, DNN is set for each specification along with other parameters. Usually, GS is carried out for logarithmic scale steps that the best combination is estimated progressively to search [16]. The obvious disadvantage of GS is its time complexity – parameter k takes different values (by assuming that n is the same for all parameters), the complexity grows exponentially at level $O(n^k)$. Random search (RS) is an alternative to GS. It integrates faster into parametricization. RS is not adaptive that it is not dynamically updated during the experiment (the solutions found did not do anything to

the search). Furthermore, there is also hybrid algorithm that combines RS with other techniques to improve its performance, for instance, manual updates provided by experts [16, 17]. The technique that has been done turns out to be not generally accepted.

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Architecture of back propagation neural network consists of several layers: input layer, hidden layer and output layer. Each neuron in each layer is connected to the next layer. The neurons in the input layer are connected to neurons in the hidden layer through synapses called as weight. In addition, hidden layers of neurons connected through synapses with neurons in the output layer. One of the neural network architectures is called as Multilayer Perceptron (MLP) [18]. MLP consists of: input layers where the neurons are fully connected to each neuron in the first hidden layer, each neuron in the hidden layer is connected to each neuron in the next hidden layer, and each neuron in the last hidden layer is fully connected with each neuron in the output layer. MLP, or often called as feedforward deep network, is a classic example of deep learning model.

Figure 1 is an example of a neural network with an MLP architecture consisting of input layers, two hidden layers, and an output layer. The closer the hidden layer to the output layer the better it identifies the complex features. For instance, MLP architecture that uses three hidden layers for face identification: the first hidden layer is used to identify the geometric shape that can distinguish the facial parts, the second hidden layer is used to identify eyes, nose, mouth, etc., and the third hidden layer is used to identify the face.

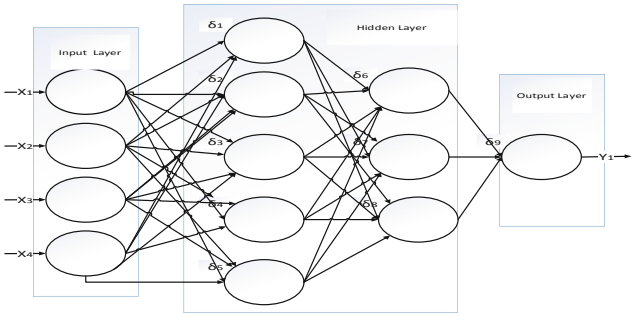

Fig. 1. Neural network

The training process for neural network is done by finding the value of each connection weight, which is done iteratively. Therefore, the output can correctly predict the target value of the training data examples. Backpropagation is an algorithm that is widely used for neural network learning, especially in MLP architecture. Each learning algorithm developed is based on inductive bias, a collection of assumptions that underlie the selection criteria of learning algorithm model. According to Mitchell [19], a learner's inductive bias is a set of additional assumptions that is sufficient to justify an inductive conclusion as a deductive conclusion. An example of an inductive bias that can be applied to MLP learning is to obtain the desired accuracy that the correct architecture must be chosen (the number of hidden layers and neurons for each hidden layer).

After obtaining the output from the perceptron based on the input given, at the error stage the perceptron calculation will be evaluated "whether the perceptron output matches the expected output or not". To calculate the difference between actual output and desired output can be used various functions of errors such as Squared Error (Eq. 1), Root Mean Squared Error (RMSE), or Cross Entropy (Eq. 2).

$$E = \frac{1}{2}\sum_{i=1}^{N}(t_i - y_i)^2 \tag{1}$$

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$$E = -\frac{1}{N}\sum_{i=1}^{N} a_i \log(y_i) + (1 - a_i)\log(1 - y_i) \tag{2}$$

where y_i is the output of the neuron to i, a_i is the *actual output* to i, and N the total number of datasets.

4 Principal Component Analysis

Principal Component Analysis (PCA) is a multivariate analysis that transforms correlated origin variables into new variables that do not correlate with each other by reducing a number of the variables mentioned, so that the variables have smaller dimension but can explain most of the diversity of the origin variables [20]. The PCA steps are as follows.

1. There is a data matrix ($X = [x_1, x_2, \ldots, x_N]$), N is the total number of samples and xi represents the sample to i.
2. Calculate the average of all samples, as follows:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{3}$$

3. Subtract all data samples with the average, as follows:

$$D = \{d_1, d_2, \ldots, d_N\} = \sum_{i=1}^{N} x_i - \mu \tag{4}$$

4. Calculate the covariance matrix, as follows:

$$\sum = \frac{1}{N-1} D \times D^T \tag{5}$$

5. Calculate the eigenvectors V and eigenvalues λ from the covariance matrix (Σ)
6. Sort the eigenvectors based on the eigenvalues that correspond
7. Select eigenvectors which have the largest eigenvalues $W = \{v_1, \ldots, v_k\}$. The selected Eigenvectors (W) represent the PCA projection space.
8. All samples are projected on the dimensional space lower than PCA (W), as follows:

$$Y = W^T D \tag{6}$$

The number of the main components formed is equal to the number of original variables. The selection of the main components used was based on the eigenvalue value that the main components will be used if the eigenvalue is greater than one. However, the reduction (simplification) of the dimension can also be done by finding the percentage criteria of the data diversity explained by the first few main components. For example, the number of the main components used was if the cumulative variance of the components was at least 70%.

5 Research Method

5.1 Research Framework

The more hidden layers in a neural network the more they can represent the increasingly complex features [19]. Deep architecture in neural network can detect features

arranged in each layer. The lower layers (that are closer to the input layer) could detect simpler features, while the layers closer to the ouput layer could detect more complex features [21]. Increasingly complex feature represents higher information content received. The high information in PCA is represented in the main component that has high variance. In other words, increasingly complex feature in hidden layers of the neural network is in accordance with the main components that have higher variance. As a result, the number of hidden layers in the required neural network will be in accordance with the number of the main components in the principal component analysis. Therefore, in this study, the number of hidden layers in the neural network could be determined based on the number of the main components formed through PCA.

5.2 Preparing the Dataset

The data set used in this study was Forest Type Mapping Data Set that was converted into numeric data. The data sets could be downloaded on UCI Machine Learning Repository website[1]. The number of input attribute was 27 and the output category was 4 classes: 's' ('Sugi' forest), 'h' ('Hinoki' forest), 'd' ('Mixed deciduous' forest), 'o' ('Other' non-forest land). The number of dataset used was 325 records, 70% of which was used as training data and the remaining is for testing. The output function used in the data set was classification.

5.3 Standardization and Normalization

Standardization was done by deleting data that had empty attributes and also eliminating extreme values. Normalization was done with the aim of getting data with attributes that are scaled accordingly. The normalization done was Min-Maks with a value between 0 and 1. Min-Maks normalization formula is as follows:

$$v' = \frac{v - min_A}{max_A\_min_A}(new\_max_A - new\_min_A) + new\_min_A \tag{7}$$

v′ = new data, v = old data, $\min_A$ = the smallest value of an attribute, $\max_A$ = the biggest value of an attribute, new_min_A = the smallest value of a new attribute (=0), new_max_A = the biggest value of a new attribute (=1).

5.4 Determining Neural Network Topology

Changing network topology was done by varying the number of hidden layers by referring to the number of the components formed in PCA. The number of hidden neurons in each hidden layer is changed by trial and error.

[1] UCI Machine Learning Repository Homepage, https://archive.ics.uci.edu/ml/datasets/Forest+type+mapping, last accessed 2019/01/10.

5.5 Training and Testing

Training was carried out with 70% data from the dataset, while testing was carried out with 30% data from the dataset. The training and testing process would stop when the iteration had reached 500 times.

6 Result and Discussion

6.1 Principal Component Anaysis Result

By analyzing the main components of the input attributes on the dataset that was going to be used for neural network training, the following results were obtained (see Table 1):

Table 1. Principal component analysis processing results

Component	Total	% of variance	Cumulative %
1	10.146	37.578	37.578
2	5.014	18.571	56.149
3	3.772	13.971	70.120
4	1.980	7.333	77.453
5	1.501	5.560	83.013
6	1.328	4.919	87.932
7	.875	3.240	91.172
8	.621	2.301	93.473
9	.511	1.893	95.366
10	.368	1.365	96.731
11	.318	1.179	97.910
12	.176	.652	98.561
13	.112	.416	98.977
14	.069	.256	99.233
15	.066	.244	99.477
16	.036	.132	99.609
17	.030	.112	99.721
18	.028	.104	99.826
19	.022	.081	99.907
20	.011	.042	99.948
21	.007	.026	99.974
22	.003	.013	99.987
23	.002	.009	99.996
24	.001	.003	99.999
25	.000	.001	100.000
26	8.995E−5	.000	100.000
27	2.354E−5	8.718E−5	100.000

If a minimum total diversity of 70% is taken, the number of hidden layers is three, if 80% of the total diversity of hidden layers is five, and if the total diversity is 90%, the number of hidden layers is seven. The number of components that will be used as the basis for determining the number of hidden layers in a neural network is chosen from one to four.

6.2 Neural Network Training Result

Neural network training was done by using multilayer perceptron architecture with the number of hidden layers chosen from one to four, while the number of neurons for each hidden layer was determined by the researcher. With the number of hidden layers selected and the number of neurons in each hidden layer determined, the neural network architecture to be trained can be seen in the following Table 2.

Table 2. The architecture of neural network

Architecture	Number of hidden layer	Number of neuron
I	1	36
II	1	100
III	2	15, 8
IV	3	15, 10, 5
V	3	20, 10, 5
VI	4	20, 15, 10, 5

The researcher gave an example as an explanation of the architecture in the above table that if architecture IV is a multilayer perceptron with three hidden layers, the first hidden layer has 15 neurons, the second hidden layer has 10 neurons, and the third hidden layer has 5 neurons. The training and testing were carried out on each of the above architectures, and the following results were obtained (see Table 3):

Table 3. The accuracy of neural network

Architecture	Accuracy
I	90.45%
II	89.17%
III	87.90%
IV	92.36%
V	92.36%
VI	27.39%

For architecture IV, the accuracy obtained was 92.36% which means that from the test data used, about 7.64% of the output was classified as incorrect.

6.3 Discussion

The experiments carried out used several different network topologies, both in terms of the number of hidden layers and neurons in each hidden layer, each of which has a certain level of accuracy by using the Forest Type Mapping dataset. From the experiments performed, it was shown that by using one hidden layer by varying the number of neurons 36(I) and 100(II), the accuracy were 90.44% and 89.18%, respectively. In the architecture of one hidden layer, the addition of the number of neurons did not increase the accuracy. For the use of two hidden layers, architecture III had an accuracy rate of 87.89% that also did not improve the accuracy compared to the use of one hidden layer. By using three hidden layers, architecture IV and V had an accuracy rate of 92.36%, which means that the use of three hidden layers was more accurate than the use of one or two hidden layers. The use of four hidden layers, in architecture VI, decreased the accuracy.

The experiments showed that the use of three hidden layers provided the best level of accuracy. If it is associated with PCA result, where it is assumed that the number of hidden layers selected was in accordance with the number of the components selected in PCA, the cumulative variance of the selected component was around 70%. This result indicated that the cumulative variance classification needed to determine the number of components does not have to be close to 100%. The classification of a group of different outputs, but still within a certain range, will be grouped in the same classification. It would be different if the regression objective function of each different output was considered as a different value.

7 Conclusion and Future Work

The right number of hidden layers chosen in neural network would provide high learning accuracy. Increasing the number of hidden layers does not guarantee an increase in their accuracy. The determination of the number of hidden layers could be done by using the number of components produced on the PCA principal component analysis by considering the cumulative variance. For the classification function, the number of cumulative variances could be done with a cut off value of 70%. For future works, the researchers need to consider the way to determine the number of neurons in each hidden layer besides determining the number of hidden layers. In addition, determining the number of hidden layers by using the number of PCA components also needs to be applied for the regression objective function. In the research that has been done, each neural network topology chosen is only conducted one-time experiments, in future studies for each topology the experiment repetition must be performed for example at least ten times, then each topology is compared. Experiments also need to be done for different types of datasets.

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Determining the Number of Hidden Layers in Neural Network by Using Principal Component Analysis

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Abstract. One of the challenges faced in the success of Deep Neural Network (DNN) implementation is setting the values for various hyper-parameters, one of which is network topology that is closely related to the number of hidden layers and neurons. Determining the number of hidden layers and neurons is very important and influential in DNN learning performance. However, up to now, there has been no guidance on it. Determining these two numbers manually (usually through trial and error methods) to find fairly optimal arrangement is a time-consuming process. In this study, we propose the method used for determining the number of hidden layers was through the number of components formed on the principal component analysis (PCA). By using Forest Type Mapping Data Set, based on PCA analysis, it was found out that the number of hidden layers that provide the best accuracy was three. This is in accordance with the number of components formed in the principal component analysis which gave a cumulative variance of around 70%.

Keywords: Neural network · Hidden layer · PCA

1 Introduction

Neural network has been successfully applied in various fields such as computer science, finance, medicine, engineering, physics, and so forth. The main reason is that neural network could approach arbitrary function. Over the past 30 years, a number of researches showed that artificial neural network called as feedforward network with one hidden layer can approach all functions arbitrarily [1–6]. One of important aspects for designing neural network is architecture or its topology that is closely related to the capability of generalization [7, 8]. Since the era of deep learning, the use of neural network that has more than one hidden layer is a research topic that caught researchers' interest. One of the challenges in the success of deep neural network implementation is setting values for various hyper-parameters, one of which is network topology that is closely related to the number of hidden layers and neurons. Determining the number of hidden layers and neurons is very important and influential in the performance of deep neural network [7, 8]. Therefore research to determine both of them is very necessary.

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According to some literatures aforementioned, determining the number of hidden layers or optimal number of neurons still has no clear guideline. Moreover, the roles and functions of both are explained minimally. Some literatures propose methods or ways to determine the number of hidden layers or neurons, but they are not generally applied due to the type of input and output data [9, 10]. Studies in this area still leave difficult research tasks [11]. Some of the methods mentioned are apparently not applicable for different types of data. The earlier researchers determined the number of hidden layers or neurons based on their experience. However, less experienced researchers even did it based on 'trial and error'. One of the methods that can be applied practically is through data mining techniques, clustering and regression [12–14]. In this study, the researcher did not explain the relationship between the number of clusters formed by feature extraction that is going to be used in machine learning process.

Although it is a difficult area of research, determining the number of hidden layers and neurons should be carried out. This is because they greatly determine the deep neural network learning performance. As a first step, a method or technique is needed to determine the number of hidden layers. Hidden layers in the neural network in stages represent increasingly complex features, while the main components of the PCA represent the information content that exists. By assuming that the complexity of features is in line with the size of the feature information, then in this study we propose a method specifically for determining the number of hidden layers in a neural network based on the number of main components formed on principal component analysis (PCA).

2 Related Work

Studies compared the use of one or two hidden layers focused on univariate and multivariate functions [4–6, 15]. Thomas [4, 5] got different result that the use of two hidden layers applied to predictive functions showed better performance. Guliyev and Ismailov [6] concluded that the use of one hidden layer was less capable of approaching the multivariate function, so the use of two hidden layers showed better performance.

To determine the number of hidden layers and neurons at once, the method is divided into two: automatically and manually [15]. Automatic determination uses models, but it also can be done without models. Manual determination uses certain formulas, some are done by trial and error. Automatic determination without a model consists of grid search (GS) and random search (RS). GS is generally used to optimize DNN parameters only if the number is very low. First, users choose a range of values to explore. Then, DNN is set for each specification along with other parameters. Usually, GS is carried out for logarithmic scale steps that the best combination is estimated progressively to search [16]. The obvious disadvantage of GS is its time complexity – parameter k takes different values (by assuming that n is the same for all parameters), the complexity grows exponentially at level $O(n^k)$. Random search (RS) is an alternative to GS. It integrates faster into parametricization. RS is not adaptive that it is not dynamically updated during the experiment (the solutions found did not do anything to

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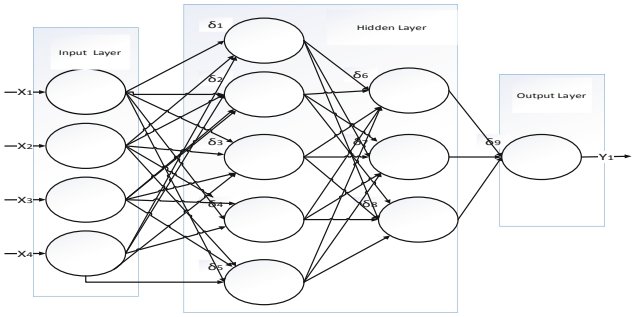

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$$E = \frac{1}{2}\sum_{i=1}^{N}(t_i - y_i)^2 \tag{1}$$

for t = actual output, y = desired output, and N = number of data, then squared errors from t and y can be calculated using Eq. 1. The use of squared error often has problems if it is implemented in the case of classification with logistical output. Unlike the squared error, cross entropy does not experience problems in this case. In cross entropy, the greater the prediction error of the neural network, the greater the update value for the weight. The error cross entropy function can be formulated as follows:

$$E = -\frac{1}{N}\sum_{i=1}^{N} a_i \log(y_i) + (1 - a_i)\log(1 - y_i) \tag{2}$$

where y_i is the output of the neuron to i, a_i is the *actual output* to i, and N the total number of datasets.

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2. Calculate the average of all samples, as follows:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{3}$$

3. Subtract all data samples with the average, as follows:

$$D = \{d_1, d_2, \ldots, d_N\} = \sum_{i=1}^{N} x_i - \mu \tag{4}$$

4. Calculate the covariance matrix, as follows:

$$\sum = \frac{1}{N-1} D \times D^T \tag{5}$$

5. Calculate the eigenvectors V and eigenvalues λ from the covariance matrix (Σ)
6. Sort the eigenvectors based on the eigenvalues that correspond
7. Select eigenvectors which have the largest eigenvalues $W = \{v_1, \ldots, v_k\}$. The selected Eigenvectors (W) represent the PCA projection space.
8. All samples are projected on the dimensional space lower than PCA (W), as follows:

$$Y = W^T D \tag{6}$$

The number of the main components formed is equal to the number of original variables. The selection of the main components used was based on the eigenvalue value that the main components will be used if the eigenvalue is greater than one. However, the reduction (simplification) of the dimension can also be done by finding the percentage criteria of the data diversity explained by the first few main components. For example, the number of the main components used was if the cumulative variance of the components was at least 70%.

5 Research Method

5.1 Research Framework

The more hidden layers in a neural network the more they can represent the increasingly complex features [19]. Deep architecture in neural network can detect features

arranged in each layer. The lower layers (that are closer to the input layer) could detect simpler features, while the layers closer to the ouput layer could detect more complex features [21]. Increasingly complex feature represents higher information content received. The high information in PCA is represented in the main component that has high variance. In other words, increasingly complex feature in hidden layers of the neural network is in accordance with the main components that have higher variance. As a result, the number of hidden layers in the required neural network will be in accordance with the number of the main components in the principal component analysis. Therefore, in this study, the number of hidden layers in the neural network could be determined based on the number of the main components formed through PCA.

5.2 Preparing the Dataset

The data set used in this study was Forest Type Mapping Data Set that was converted into numeric data. The data sets could be downloaded on UCI Machine Learning Repository website[1]. The number of input attribute was 27 and the output category was 4 classes: 's' ('Sugi' forest), 'h' ('Hinoki' forest), 'd' ('Mixed deciduous' forest), 'o' ('Other' non-forest land). The number of dataset used was 325 records, 70% of which was used as training data and the remaining is for testing. The output function used in the data set was classification.

5.3 Standardization and Normalization

Standardization was done by deleting data that had empty attributes and also eliminating extreme values. Normalization was done with the aim of getting data with attributes that are scaled accordingly. The normalization done was Min-Maks with a value between 0 and 1. Min-Maks normalization formula is as follows:

$$v' = \frac{v - min_A}{max_A\_min_A}(new\_max_A - new\_min_A) + new\_min_A \tag{7}$$

v′ = new data, v = old data, $\min_A$ = the smallest value of an attribute, $\max_A$ = the biggest value of an attribute, new_min_A = the smallest value of a new attribute (=0), new_max_A = the biggest value of a new attribute (=1).

5.4 Determining Neural Network Topology

Changing network topology was done by varying the number of hidden layers by referring to the number of the components formed in PCA. The number of hidden neurons in each hidden layer is changed by trial and error.

[1] UCI Machine Learning Repository Homepage, https://archive.ics.uci.edu/ml/datasets/Forest+type+mapping, last accessed 2019/01/10.

5.5 Training and Testing

Training was carried out with 70% data from the dataset, while testing was carried out with 30% data from the dataset. The training and testing process would stop when the iteration had reached 500 times.

6 Result and Discussion

6.1 Principal Component Anaysis Result

By analyzing the main components of the input attributes on the dataset that was going to be used for neural network training, the following results were obtained (see Table 1):

Table 1. Principal component analysis processing results

Component	Total	% of variance	Cumulative %
1	10.146	37.578	37.578
2	5.014	18.571	56.149
3	3.772	13.971	70.120
4	1.980	7.333	77.453
5	1.501	5.560	83.013
6	1.328	4.919	87.932
7	.875	3.240	91.172
8	.621	2.301	93.473
9	.511	1.893	95.366
10	.368	1.365	96.731
11	.318	1.179	97.910
12	.176	.652	98.561
13	.112	.416	98.977
14	.069	.256	99.233
15	.066	.244	99.477
16	.036	.132	99.609
17	.030	.112	99.721
18	.028	.104	99.826
19	.022	.081	99.907
20	.011	.042	99.948
21	.007	.026	99.974
22	.003	.013	99.987
23	.002	.009	99.996
24	.001	.003	99.999
25	.000	.001	100.000
26	8.995E−5	.000	100.000
27	2.354E−5	8.718E−5	100.000

If a minimum total diversity of 70% is taken, the number of hidden layers is three, if 80% of the total diversity of hidden layers is five, and if the total diversity is 90%, the number of hidden layers is seven. The number of components that will be used as the basis for determining the number of hidden layers in a neural network is chosen from one to four.

6.2 Neural Network Training Result

Neural network training was done by using multilayer perceptron architecture with the number of hidden layers chosen from one to four, while the number of neurons for each hidden layer was determined by the researcher. With the number of hidden layers selected and the number of neurons in each hidden layer determined, the neural network architecture to be trained can be seen in the following Table 2.

Table 2. The architecture of neural network

Architecture	Number of hidden layer	Number of neuron
I	1	36
II	1	100
III	2	15, 8
IV	3	15, 10, 5
V	3	20, 10, 5
VI	4	20, 15, 10, 5

The researcher gave an example as an explanation of the architecture in the above table that if architecture IV is a multilayer perceptron with three hidden layers, the first hidden layer has 15 neurons, the second hidden layer has 10 neurons, and the third hidden layer has 5 neurons. The training and testing were carried out on each of the above architectures, and the following results were obtained (see Table 3):

Table 3. The accuracy of neural network

Architecture	Accuracy
I	90.45%
II	89.17%
III	87.90%
IV	92.36%
V	92.36%
VI	27.39%

For architecture IV, the accuracy obtained was 92.36% which means that from the test data used, about 7.64% of the output was classified as incorrect.

6.3 Discussion

The experiments carried out used several different network topologies, both in terms of the number of hidden layers and neurons in each hidden layer, each of which has a certain level of accuracy by using the Forest Type Mapping dataset. From the experiments performed, it was shown that by using one hidden layer by varying the number of neurons 36(I) and 100(II), the accuracy were 90.44% and 89.18%, respectively. In the architecture of one hidden layer, the addition of the number of neurons did not increase the accuracy. For the use of two hidden layers, architecture III had an accuracy rate of 87.89% that also did not improve the accuracy compared to the use of one hidden layer. By using three hidden layers, architecture IV and V had an accuracy rate of 92.36%, which means that the use of three hidden layers was more accurate than the use of one or two hidden layers. The use of four hidden layers, in architecture VI, decreased the accuracy.

The experiments showed that the use of three hidden layers provided the best level of accuracy. If it is associated with PCA result, where it is assumed that the number of hidden layers selected was in accordance with the number of the components selected in PCA, the cumulative variance of the selected component was around 70%. This result indicated that the cumulative variance classification needed to determine the number of components does not have to be close to 100%. The classification of a group of different outputs, but still within a certain range, will be grouped in the same classification. It would be different if the regression objective function of each different output was considered as a different value.

7 Conclusion and Future Work

The right number of hidden layers chosen in neural network would provide high learning accuracy. Increasing the number of hidden layers does not guarantee an increase in their accuracy. The determination of the number of hidden layers could be done by using the number of components produced on the PCA principal component analysis by considering the cumulative variance. For the classification function, the number of cumulative variances could be done with a cut off value of 70%. For future works, the researchers need to consider the way to determine the number of neurons in each hidden layer besides determining the number of hidden layers. In addition, determining the number of hidden layers by using the number of PCA components also needs to be applied for the regression objective function. In the research that has been done, each neural network topology chosen is only conducted one-time experiments, in future studies for each topology the experiment repetition must be performed for example at least ten times, then each topology is compared. Experiments also need to be done for different types of datasets.

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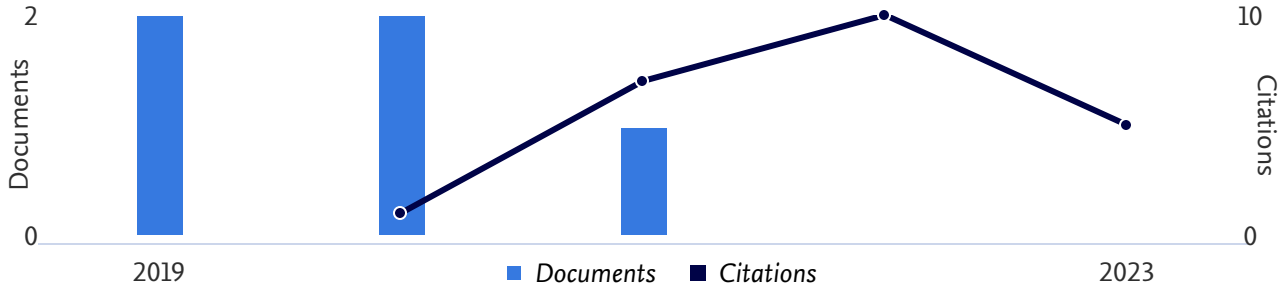

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