Journal of Asian Scientific Research
ISSN(e): 2223-1331
ISSN(p): 2226-5724
DOI: 10.18488/journal.2.2017.711.450.458
Vol. 7, No. 11, 450-458

URL: www.aessweb.com

A REVIEW ON CLASSIFICATION OF THE URBAN POVERTY USING THE ARTIFICIAL INTELLIGENCE METHOD

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Article History
Received: 21 August 2017
Revised: 17 November 2017
Accepted: 24 November 2017
Published: 30 November 2017

Keywords
Urban poverty
Artificial intelligence

ABSTRACT

Poverty and how it has been assessed and measured is a frequently discussed topic by policy makers and social developers. The identification process in poverty measurement is indeed essential towards acknowledging the poor in the population; hence this needs to be clarified. Malaysia measures poverty by means of poverty line, indicating the unidimensional and inflexible distribution of poor and non-poor especially in urban areas. Many researchers have used fuzzy logic to solve the problem of rigid poor/non-poor dichotomy. This current trend has been able to augment the gap between the rigid and inflexible classification of poor and non-poor. However, there are still several shortcomings that need attention. For instance, the classification of the poor in fuzzy logic that is based on the average income of households still does not cover on the different range of disadvantage on non-monetary items. Based on these trends, ANFIS is proposed to resolve on the highlighted issues. The winning features of ANFIS, which include on simplicity in implementation, understandable explanation facilities through fuzzy rules, and ease of incorporation of both linguistic and numeric knowledge for problem solving may help in producing better result in classification of the urban poor. Essentially, the neural network is proposed to complement the fuzzy system, hence overcoming the limitations of both fuzzy systems and neural networks. As such, ANFIS method is used in this study to better classify on the poor and non-poor compared to fuzzy rule-based system which is lacking in prediction error rate due to too many variables used. However, this method deteriorates from misclassified poverty indicators; hence this study proposed on ensemble ANFIS to produce more accurate and robust classification results. An ensemble model is usually employed to address the problems of over-fitting, high dimensionality or missing features in the training data. Generally, combining multiple classification models increases predictive performance compared to the use of an individual model alone. Therefore, based on these current trends, this study is aimed to do a review on classification of the urban poverty using the artificial intelligence method.

Contribution/ Originality: This study contributes in the existing literature of state-of-the-art urban poverty classification methods from the perspective of the modern Artificial Intelligence approach, which is compared with the conservative econometric model. In addition, the implementation of ANFIS and classification ensemble learning in urban poverty classification are also briefly discussed.

1. INTRODUCTION

Poverty and how it has been assessed and measured is a frequently discussed topic by policy makers and social developers. Poverty measurement is highly dependent on the definition of poverty, income, poverty line, and the approaches used [1]. The identification process in poverty measurement is indeed essential towards acknowledging the poor in the population; hence this needs to be clarified. Malaysia is still using the traditional absolute poverty line, which involves household standard minimum income or consumption [2-6]. However, the definition of poverty has changed over time, hence, shedding the doubt on the credibility of the progress of measuring the poor in the population.

The econometrics estimation approach has rarely been discussed with the Artificial Intelligence approach when poverty is involved. Econometric models are simulation models, which are based on the theoretical ideas of economic modelling structural constraints and their behaviour when the equilibrium state changes [7]. The problem lies in the interpretation of the results rendered by the model. Some of the conventional econometrics approaches for predicting poverty indicators include the Poverty Assessment Tool, Zeller, et al. [8] model-based approach [9] and poverty mapping, consisting various methods such as small-area estimation [10] and direct measurement of household-survey data [11]. Nonetheless, recently, the application of Artificial Intelligence methods has made waves in the economic welfare field, fusing both areas into comprehensive studies. Compared to the conventional econometrics approach, the Artificial Intelligence approach is more flexible towards changes happening in the model.

This paper aims to provide better understanding of urban poverty, whilst reviewing several works on the poverty measurement approaches. The remainder of this paper is structured as follows: Section 2 describes on the determination of poverty using the artificial intelligence method. Section 3 describes on the state of the art of Adaptive Neuro Fuzzy Inference System (ANFIS). This is followed by the review of classification ensemble methods in urban poverty. The paper is then concluded ~~then~~ in Section 5.

2. DETERMINATION OF POVERTY USING ARTIFICIAL INTELLIGENCE METHOD

Poverty indicates deprivation of crucial basic needs; hence, the concept varies with respect to the qualitative and quantitative values that may change within a particular population. An early research by Sen [12] as cited in Gopal and Malek [2] stresses that poverty is a multidimensional phenomenon, hence this is the proposition that most economists have to accept theorically. Many researchers have used fuzzy logic to solve the rigid poor/non-poor dichotomy. A study by Belhadj [13] highlighted the use of fuzzy logic in both unidimensional and multidimensional poverty measurements by classifying poverty into three levels. The paper defined three levels of poverty: i) income below the poverty line; ii) income between the minimum and maximum threshold; and iii) income above the maximum value. Belhadj and Limam [14] extended this study, focusing on multidimensional poverty and the use of fuzzy logic as a useful tool for analysis in viewing deprivation. Their study aimed to provide deprivation quantitative expressions and determination of the intensity for particular poor households. Both these studies used Tunisian households in the year 1990 as their source of data.

In line with these works, Othman, et al. [5] proposed the fuzzy index poverty model in the Malaysian context, in which a composite of multidimensional indicators is introduced. Their study showed the use of Fuzzy Poverty Index to determine several poverty indicators, which use the living conditions of households in rural areas of Terengganu. Based on this idea, Abdullah [1] proposed three membership functions (e.g. exponential, trapezoidal, quadratic sigmoid functions) to suggest the poverty line and its application for Malaysian data. His study used the relative poverty approach in identifying the poor by setting the poverty line. According to Abdullah [1] this study is applicable for fuzzy set theory and as an extended version of previous researches done by Betti and Verma [15] as well as Cerioli and Zani [16]. However, the study neglected the minimum food and non-food items and was solely dependent on the highest and lowest household income, turning all poverty elements into one singular variable.

Ruslau and Ulama [17] classified the poverty among Javanese in Indonesia using a neural network method. Their study experimented with 65 households, classifying them into appropriate poverty statuses. Ruslau and Ulama [17] used 16 predictor variables in this study, consisting ~~of~~ one ordinal variable, three internal variables, and a nominal variable. These variables are trained using a back-propagation algorithm. Even though the classification accuracy is not significantly improved, the network integration applied in this study has helped reduce the error rates and improved the overall accuracy of heterogeneous and big data. Pareek and Prema [18] used a multi-layer perceptron network to classify the poor in India. Their study used 13 deprived variables for testing, including the availability of clothing, food security, literacy status, and type of indebtedness. This study also experimented with different numbers of hidden layers, number of nodes in the hidden layers, and the activation function. Each experiment showed a certain percentage of misclassified households, hence leaving rooms of improvement for future work in this area.

In addition, Lucchini and Assi [19] proposed a self-organising map neural network, using data drawn from the 2009 Swiss Household Panel. This study aimed to identify homogenous clusters of individuals characterised by 44 deprived indicators and well-being. The dimensions measured in this study included happiness, health, relational support, trust toward people and institutions, satisfaction with free time, housing, neighbourhood environment, material deprivation, and financial problems. The study proved that clustering procedures can be applied with non-monetary indicators to contribute towards a comprehensive and real picture of public conditions. On the other hand, Magdalena, et al. [20] arrived at an opposite solution. Their study forecasted public expenditure using a feed forward neural network, worked as a base for the analysis of potential budgetary implications. Their study analysed the correlation between public expenditure functions and GDP growth in selected Central and Eastern European countries. Magdalena, et al. [20] built a model that could be applied to all five countries selected in their study (e.g. Hungary, Poland, Czech Republic, Bulgaria, and Romania) to observe the differences in the patterns of expenses, their influence factors, and their impact on economic growth in the future. Based on this study, most of the public is observed to spend on social protection, health, education, and general public services.

In tandem with multidimensional poverty problems, Zeumo, et al. [21] proposed clustering techniques derived from data analysis and a multi-attribute decision analysis approach as a solution. The study focused on the concept of meaningful multidimensional poverty measurement (MDPM) by combining the economic capability approach and decision-making methodology. However, this study provided only a simple illustrative example to represent the new method with no real-life case study. On the other hand, Shekarian and Gholizadeh [22] focused on predicting the key element that contributes to the deprivation of a household using an Adaptive Network Based Fuzzy Inference System (ANFIS). Their study used real micro data including some elements in households and housing units in the urban areas of Esfahan, Iran. To date, there has been no poverty and welfare analysis that has applied the ANFIS method; hence, their study was the first to combine both the welfare measure of Sen [12] and ANFIS to identify the role of certain socio-economic factors in household welfare.

3. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

In fuzzy systems, the rule base can be created from expert knowledge and then used in specifying fuzzy sets to partition all variables and fuzzy rules, so as to describe the input/output relationship of the problem at hand. This appears to be one of the advantages of this soft computing method [23]. However, the inclusion of knowledge experts alone would only lead to manual tuning in the design stage, which involves modifying membership functions and/or rule base of the fuzzy systems. This is due to the lack of knowledge regarding fuzzy systems among knowledge experts, resulting in the wrong location of fuzzy sets and number of rules [24]. Therefore, this will result in too much time consumption and error-prone manual tuning on behalf of the knowledge experts.

Moreover, not all knowledge experts can be found in all domains. Hence, the automation of learning process using the available data sample is important to support the definition of the fuzzy rule base. This can be ~~is~~ made possible in the learning procedure by tuning the fuzzy inference systems as a parametric model.

In the design of intelligent systems, both fuzzy logic and artificial neural networks are complementary [25]. These two technologies are seen to be promising in intelligently capturing the characteristics of human brain. Both of them have their own pros and cons. As they are integrated, the system will have the pluses of both neural networks (e.g. learning and optimisation ability and connectionist structures) and fuzzy system (human-like IF-THEN) rules thinking and flexibility in including expert knowledge.

In summary, neural networks can improve their transparency, making them closer to fuzzy systems, while fuzzy systems can self-adapt, making them closer to neural networks [26]. Most of the learning algorithm in the local modelling domain developed an extended version of neural networks to be able to incorporate or fine tune fuzzy systems. These methods manipulate on the layered architecture of fuzzy logic, which is similar to neural networks. By doing so, the fuzzy system becomes a neuro-fuzzy system, i.e. special neural network architecture. One neuro-fuzzy network example was developed by Jang [27] named the Adaptive Network-based Fuzzy Inference System (ANFIS). The ANFIS is one of the popular Artificial Intelligence model that incorporates the best of neural network and fuzzy model. The Takagi-Skeno fuzzy system is implemented in ANFIS model for its network architecture. This algorithm used on the combination of plain back-propagation and Least Mean Square approach to train the system. The fuzzy if-then rules are used in ANFIS to portray the relationships between variables. Therefore, this model can interpret the obtained results, which is not possible with other structures such as neural networks [28]. ANFIS is also one of the best models in estimating the function of other neuro-fuzzy models. ANFIS applies neural learning rules to identify and tune the parameters and structure of a Fuzzy Inference System (FIS).

There are several advantages of the ANFIS, which make it a popular algorithm to be used on various scientific applications. The winning features of an ANFIS include: simplicity in implementation, fast and accurate learning, strong generalisation abilities, and understandable explanation facilities through fuzzy rules, and ease of incorporation of both linguistic and numeric knowledge for problem solving. Essentially, the neural network is proposed to complement the fuzzy system, hence overcoming the limitations of both fuzzy systems and neural networks [29]; [30]. The network can be regarded both as an adaptive fuzzy inference system with the capability of learning fuzzy rules from data, and as a connectionist architecture provided with linguistic meaning.

4. CLASSIFICATION ENSEMBLE

The ensemble method has been gaining popularity recently, due to its accurate and robust models that can be largely applied in predictive modelling tasks. A classification ensemble is a predictive model comprising a weighted integration of multiple classification models. The idea behind ensembles is to maximise overall predictive power by combining the predictions of the individual base models. Generally, combining multiple classification models increases predictive performance compared to the use of just an individual model. These are usually employed in the context of the learning tasks of classification and regression to address the problems of over-fitting, high dimensionality, or missing features in the training data. Theoretically, ensemble methods consist of two main components: i) a technique for learning a set of candidate base models; and ii) a combining scheme specifying how the base model predictions are being aggregated into an ensemble prediction.

Based on recent studies, ensembles can be categorised into: i) homogeneous and ii) heterogeneous based on how the base models are learned [31]. In the homogeneous ensemble, the base models are learned with the same learning algorithm, differing by sampling variants including: i) sampling of data instances (e.g. bagging, boosting); ii) sampling of data features (e.g. random subspace) [32] or iii) both bagging random subspace [33] and random forests [34]; [35]. On the other hand, in heterogeneous ensembles, different learning algorithms are combined to build the base model [35]. This study focuses on the homogeneous ensemble whereby the base model is the same. Figure 1summarises the classifications of base models based on how they are learned.

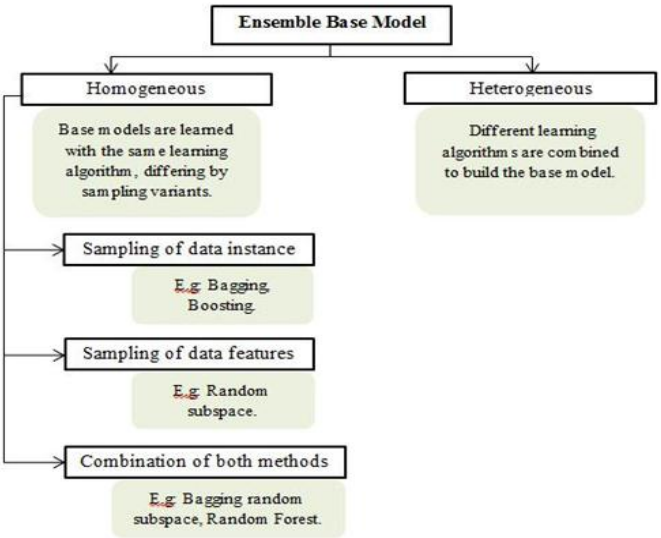

Figure-1. Classification of ensemble base learners based on how they are learned.

There are two popular ensemble learning techniques, as briefly described in Figure 2, which are: i) Bagging and ii) Boosting. The pioneer and simplest ensemble learning method is bagging, or also known as bootstrap aggregation, which was developed by Breiman [36]. In bagging, the random samples of training data are generated from the sample data with replacements, which are used to learn the ensemble instances.

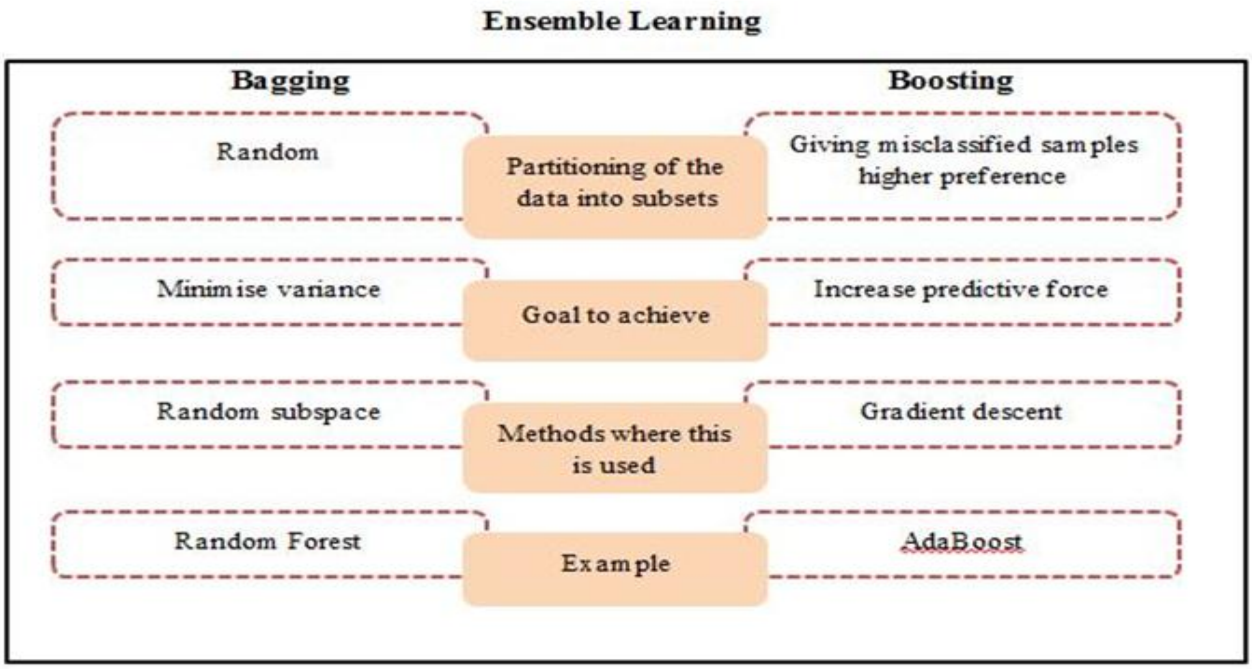

Figure-2. Comparison of ensemble learning.

The over fitting problem in unstable models has been successfully overcome in bagging ensembles. Nevertheless, this ensemble is not that accurate when constructed with stable models. On the other hand, boosting refers to a more developed ensemble method, which combines several weak base learners across different distributions of the training data. Freund and Schapire [37] first developed the AdaBoost algorithm, which ~~is~~ was an implementation of the boosting method in the classification of ensembles. Similar to bagging, AdaBoost also resampled training data. However, AdaBoost prioritised more informative data, thus changing the distribution for the subsequent iteration of training of the model. In this way, the individual weak predictors will focus on different instances, and their integration will be more robust. Later, Breiman [36] developed the Random Forest as an improvement upon the bagging method, by combining tree predictors such that each level of trees will depend on the values of features sampled independently; hence, producing better results than the former ones.

Classification ensemble methods can be categorised by the ways they are built [38]. Specifically, Kuncheva [38] defined four dimensions for characterising ensemble methods: integration level, classifier level, feature level, and data level. Therefore, this study will focus on the integration level that deals with the ways the classifier decisions are integrated. Subsequently, the predictions of classification base learners models that predict qualitative values are usually integrated using different voting schemes. On the other hand, the output of base learner models that predict single numeric values for a given input can be integrated using the aggregation functions of average, weighted average, and weighted median [39].

The objective of this study is to provide input for a quantitative poverty of an urban area, therefore the aggregation method of ensembles is highlighted. This study extends the related studies in state-of-the-art ensemble learning, with ANFIS as the base learner in various domains. There are several recent studies in a variety of domains, which present the classification of ensembles and their integration methods. Melin, et al. [40] increased their training complexity in ensemble integration using different types of membership functions and the setting up of their desired goal error. This study shows that the combination of learned ensemble using the AdaBoost algorithm and ANFIS as the base learner in a chaotic time series will help minimise prediction errors. This study compared three time series, namely the Mackey-Glass, Dow Jones, and Mexican Stock Exchange. The ensemble integration used in this study is the integration by mean and integration by weighted mean.

In the medical decision-making domain, Akdemir, et al. [41] presented a new method based on combining principal component analysis (PCA) and ANFIS to diagnose optic nerve disease from visual-evoked potential (VEP) signals. Their study aimed to improve the classification accuracy of the ANFIS classifier for the diagnosis of optic nerve disease from VEP signals. Their study experimented with three types of ensemble integration methods, which ~~are~~ were the proposed weighted arithmetical mean, standard arithmetical mean, and geometrical mean. The results showed that the proposed classifier ensemble approach based on ANFIS trained with different train-test datasets and PCA successfully produced very promising results in the diagnosis of optic nerve disease from VEP signals. Canul-Reich, et al. [42] on the other hand, used the bagging algorithm to learn the ensemble with ANFIS as the base learner. Their study compared the ensemble of ANFIS classifiers with the standard ANFIS, resulting in a higher accuracy of predictive performance for the former method.

Moreover, Lei and Wan [43] in their environmental protection study, proposed an architecture for the ensemble ANFIS (EN-ANFIS) to forecast the Air Pollution Index (API) in Macau. Their paper used the bootstrap sampling with replacement method and random sample without replacement method to construct the subsystems in the proposed ensemble learning classifier. The experimental results showed that the proposed EN-ANFIS structure not only performed much better than any ANFIS units, but also obtained an equivalent performance in comparison to the conventional ANFIS. This study has proven that the proposed method showed great ability in handling nonlinear problems while considering the complicated structure of environmental data used.

The current study is clearly related to the learning ensembles for tackling various predictive modelling tasks in different poverty domains. Otok and Seftiana [44] aimed to improve the classification of poor households in Jombang, Indonesia, using the Classification and Regression Tree (CART) approach combined with the Random Forest method (RF-CART). The classification analysis for the Jombang regency was classified into Poor Households and Chronically Poor Households based on expected household assistance, which is obtained based on the poverty indicator factors such as health, education, social, economy, and human resources. Their study concluded that the proposed RF-CART method outperformed the standard CART method in classifying the poor households in Jombang, as it increased the classification accuracy rate of both Poor Households and Chronically Poor Households. Furthermore, Thoplan [34] also proved that the Random Forest ensemble method, which comprised the bootstrapping and voting method, performed better in classifying the poor in Mauritius. Their study included the number of hours worked, age, education, and gender as the most important variables in the classification of the poverty status of an individual. The Random Forest classification is used to categorise people below and above the relative poverty line. Therefore, their study considered a poor person in the year 2000 as someone whose income is below Rs 2800. Interestingly, Thoplan [34] observed that there was a poverty gender-gap in his study, whereby males had a lower tendency of being classified as poor as compared to females. As such, their study also highlighted the better accuracy of the proposed method with respect to the applied Mauritius census data.

5. CONCLUSION

In conventional method, the classification of the urban poor is based on the monetary values, regardless of the individual wellbeing and social arrangements of the household. However, the method suffers from the insufficient multidimensional urban poverty knowledge. Several efforts have been made in multidimensional urban poverty classification by using artificial intelligence methods by local researchers [1]. This study provides an extensive review of state-of-the-art urban poverty classification methods from the perspective of the modern Artificial Intelligence approach, which is compared with the conservative econometric model. Furthermore, ANFIS and classification ensemble learning are also briefly discussed in this study.

Funding: This research is supported by the MyPhD scholarship scheme of the Ministry of Higher Education Malaysia and the G-Heart scheme under Gates Scholars Foundation. The appreciation is also dedicated to publication fund by Vot no: 14H34 and 4F744 from Ministry of Higher Education Malaysia and RMC UTM.
Competing Interests: The authors declare that they have no competing interests.
Contributors/Acknowledgement: All authors contributed equally to the conception and design of the study.

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