Classification of surface condition of flexible road pavement using Naïve Bayes theorem

A T Olowosulu¹, J M Kaura¹, A A Murana¹ and P T Adeke²*

¹Department of Civil Engineering, Faculty of Engineering, Ahmadu Bello University Zaria, Kaduna State, Nigeria
²Department of Civil Engineering, College of Engineering, Federal University of Agriculture Makurdi, Benue State, Nigeria

*Corresponding Author’s email: adeke.pt@outlook.com

Abstract. Data collection, availability and accuracy on road pavement surface condition have been identified as the major setback for pavement management system in low and medium income countries. This situation necessitates the adoption of historic dataset which often is characterised by missing and noisy data elements. The Naïve Bayes theorem which depends on conditional probabilities of prior events or attributes for condition classification and prediction was used to investigate the authenticity of surface condition classification of flexible road pavement. Some selected links of Federal Highways in Nigeria based on the availability of historic dataset were considered. The Naïve Bayes theorem as a data mining approach was implemented using Waikato Environment for Knowledge Analysis (WEKA) software which performed satisfactorily in surface condition classification with minimal margin of errors due to its ability to handle challenges of missing and noisy dataset. Results of classifications indicated that; links 716, 5, 8, 22 and 136 in Borno, Kwarara, Lagos, Oyo and Plateau states respectively had relatively high level of unworthiness as at the time the data was collected, hence call for immediate maintenance and rehabilitation actions, while links 89, 375, 370, 130, 17, 332, 138, 144 and 255 from Anambra, Bendel, Imao, Kaduna, Ogun, Plateau, Rivers and Sokoto states respectively were worthy and had no cause for immediate maintenance.

Keywords: Pavement Surface condition, Data mining, Naïve Bayes theorem, WEKA Software.

1. Introduction

The choice of flexible road pavement for highway construction in low and medium income countries is due to its relatively cheap cost of construction, maintenance and rehabilitation [1][2]. The management of road pavement system requires periodic surface condition assessment and classification for optimum maintenance strategy [3][4]. In most cases, the act employs manual approaches which are associated with subjective measurements by trained personnel whose reportage are prone to significant errors due to physical limitations and human intuitive reasoning. The aim of developing road pavement management system is to build and maintain road facilities that can cater for the fast growing human population and corresponding travel demand over time [5]. Since road infrastructures deteriorate over time, hence the need for effective planning and efficient management system arises [6][7][8]. The culture of investigating and classifying road pavement condition periodically for timely scheduling of repairs is essential for achieving reliable road network that could connect people and places, based on proper planning, timely maintenance and rehabilitation actions, budgetary allocation and execution to aid socio-cultural, administrative and economic activities in the country [9][10][11]. The major disadvantages of flexible pavement are its relatively short life cycle and rapid deterioration over time which leads to reduction in performance index due to the impact of damaging factors [12][13][14]. The rate of deterioration of flexible road pavement which shortens its life cycle is a function of several factors such as; traffic load, climatic condition (rain, temperature, etc.), material properties, drainage condition, maintenance policy, design of pavement structure and workmanship, etc. [8] [10][15] [16][17]. Because huge funds are required for highway construction and maintenance.
practices, periodic and timely maintenance strategies are essential for efficient management system [13][18][19][20][21][22][23][24][25][26].

The assessment of pavement performance usually employs different engineering techniques that require field data generated on-site using manual or automated methods, or obtained from database of pavement management agencies, or from experienced engineers working on pavement distresses [18][27]. According to [3] and [28], the investigation of pavement behaviour using insufficient or incomplete dataset necessitate basic assumptions and engineering judgement which may be misleading so often. The performance of road pavement could be classified on a scale of good to worse. The classification is a function of the severity level, quantity and frequency of surface defects caused by deterioration of the pavement materials and its drainage condition [3][29][30]. The periodic deterioration and consequent failure of road pavement has become a serious concern to road management agencies, since it necessitate initial condition classification for accurate performance prediction over time and planning for repairs [29][31]. This therefore requires accurate condition classification and performance prediction for effective road management decision [12][13][14][25][32][33].

Following the rapid technological advancement in recent times, the use of intelligent algorithms known as Artificial Intelligence (AI) techniques for developing pavement management tools has become a common research methodology [4][17][18][25][34][35]. This intelligent approach employs methods of machine learning or data mining (knowledge discovery) for analysing system behaviour [31][36][37][38][39][40][41]. Data mining is a mathematical technique used for examining hidden relationship between variables in a dataset [18][42]. It is a machine learning technique which has gained acceptance from many researchers of different fields [43]. Examples of data mining methods include; Rough Set theory, Artificial Neural Network (ANN), Decision Tree, Support Vector Machine, Bayesian models (Naïve Bayes), etc. [18][44][45].

Data mining techniques are capable of analysing problems characterised by imprecise, uncertain or incomplete dataset and knowledge based elements with associated attributes to discover patterns and relationship between elements [18][41][44][46][47][48]. Other functions of the algorithms include to identify partial or total dependencies in a given dataset, eliminate redundant data, give approach to null values, missing data, dynamic data, etc. They are suitable for sourcing core information in a relatively poor dataset generated from system behaviour such as pavement condition for the purpose of performance prediction.

Before the adoption of any road pavement maintenance model or performance predictions are made, it is required that the initial surface condition be known [17][49][50]. Surface condition classifications are usually based on pavement surface distress indices such as; Condition Rating Survey (CRS), Pavement Condition Index (PCI) [25][30], International Roughness Index (IRI) [51], Condition Survey Rating Scores (CSRS) [3], etc. The measurement of these parameters requires the assessment of pavement surface distress attributes such as; cracks, potholes, rutting, roughness, drainage condition, etc. over time. In most instances, the major challenge associated with pavement management systems include data collection, availability and accuracy which necessitate adoption of historic or existing dataset which defines its behavioural attributes that were generated by individuals whose degree of accuracy of subjective measurements may be unknown or questionable [5][29]. In addition to challenges associated with data gathering and processing in developing countries like Nigeria, such data are prone to significant errors (noise and outliers) that may be hiding and misleading in the interpretations of performance attributes, hence requires processing using advanced analytical techniques for cleansing to help reduce margin of error from the subjective estimations on the field [5].

This therefore necessitate the use of intelligent algorithms of data mining techniques such as the Naïve Bayes classifier. It is an intelligent algorithms which is capable of handling the imprecise (vagueness) or inaccurate dataset on road pavement surface condition for better initial condition classification to pave the way for accurate prediction of future condition.

Though several data mining techniques such as Decision Trees, Support Vector Machine, Neural Networks and Meta-algorithms were employed for inverse analysis of pavement response to load effect in order to overcome limitations of the conventional backcalculation of analysing pavement moduli in
techniques like the Random SubSpace, Rough Set theory, Pace Regression, etc. are also recommended for pavement analysis [18]. The choice of Naïve Bayes algorithms for this study was based on it relatively high sensitivity to missing data which affects estimation of prior probabilities during classification runs, hence results to accurate and reliable classification outputs [5].

1.1. Naïve Bayes Theorem
This algorithm is based on the Bayesian probability theory which operates on conditional rules [5][31]. It is a naive approach which uses conditional probabilities of prior events classified by attributes of a class label for making predictions or classifications of the targeted attributes. The Naïve Bayes algorithm is mostly used for predictive modelling using discrete events of a database without missing data to predict class labels [52]. The discretization of continuous dataset is required in order to suite the Naïve Bayes algorithm or classifier [53]. The model computes or predicts probability of an attribute belonging to a given class based on the assumption that the effect of the attribute is independent of the other attributes in the same class, hence is known as class conditional independence model [54]. According to [52] the Bayes theorem calculates the probability of a targeted attribute or classification by counting the frequency and combinations of values in the dataset, then estimating the parameter using method of maximum likelihood. The algorithm suites most complex real life problems. Also, its ability to estimate the parameter using small amount of training data is considered the major advantage of the Naïve Bayes algorithm. But its robustness is affected by noisy element in the dataset. The formate of dataset used for prediction and classification problems assumed the format shown in equation (1):

\[ y = f(x_1, x_2, x_i, \ldots) \]

where \( y \) is the target or classification and \( x \) is an array of independent attributes used for condition prediction or classification. According to [55], the Naïve Bayes model is expressed as shown in equation (2):

\[ P(y|x) = \frac{P(x|y)P(y)}{P(x)} \]

where \( P(y|x) \) is the posterior probability of class \( y \) (target) given the predictor \( x \) (attribute), \( P(x) \) is the prior probability of predictor, \( P(y) \) is the prior probability of class and \( P(x|y) \) is the measure of maximum likelihood or probability of predicting a given class label.

Generally, previous studies on the use of probability theorems for pavement management system have recorded successes [56][57][58][59]. The use of Naïve Bayes algorithm as reported in [31], and [5] also confirm the assertions. Though its inability to handle missing and noisy data elements yields results with relatively significant margin of error [29][52][55][60], estimations of the Naïve Bayes approach are relatively more reliable.

Data classification using the Naïve Bayes theorem could be implemented in the Waikato Environment for Knowledge Analysis (WEKA) software [61][62]. It is a data mining toolkit developed at the Waikato University, New Zealand. It is an open source software written in Java programming language, used for research and project works [63]. The software is capable of carrying out data mining in the form of data pre-processing, classification, visualisation, association, clustering and filtering [64][65]. Algorithmic models used by WEKA for behavioural classification and predictions of systems behaviour include the Random Forest, Naïve Bayesian, Decision Tree (J48), etc.

The aim of this study therefore is to investigate surface condition classification of flexible road pavement using Naïve Bayes theorem. The objective of the study is to adopt historic dataset and apply the Naïve Bayes classifier for surface condition classifications based on surface distresses implemented using the WEKA software.

2. Methodology
2.1. Study Area
Nigeria is among the most populous countries on the Africa continent with an estimated human population of 180 million. Its land mass is estimated at 923.7768 square kilometres area [66], upon
which her roads are constructed. Properties of some Federal Highway links in Nigeria considered by this study are as presented in Table 1.

| S/N | State   | Link ID | Length (km) | No. of Sections | Age (Years) | Surface Finishing           |
|-----|---------|---------|-------------|-----------------|-------------|-----------------------------|
| 1.  | Anambra | 89      | 43.7        | 106             | 6           | Asphalt concrete            |
| 2.  | Bauchi  | 285     | 51.3        | 77              | 8           | Asphalt concrete            |
| 3.  | Bendel  | 375     | 69.0        | 142             | 6           | Asphalt concrete            |
| 4.  | Borno   | 716     | 50.7        | 173             | 9           | Surfaced dressed            |
| 5.  | Imo     | 370     | 45.6        | 47              | 2           | Asphalt concrete            |
| 6.  | Kaduna  | 130     | 46.8        | 123             | 5           | Asphalt concrete            |
| 7.  | Kwara   | 5       | 22.8        | 74              | 9           | Asphalt concrete            |
| 8.  | Lagos   | 8       | 8.1         | 27              | 6           | Asphalt concrete            |
| 9.  | Ogun    | 17      | 18.3        | 61              | 12          | Asphalt concrete            |
| 10. | Ogun    | 332     | 30.9        | 105             | 10          | Asphalt concrete            |
| 11. | Oyo     | 22      | 23.4        | 56              | 10          | Asphalt concrete            |
| 12. | Plateau | 136     | 10.0        | 24              | 9           | Asphalt concrete            |
| 13. | Plateau | 138     | 23.2        | 59              | 5           | Asphalt concrete            |
| 14. | Rivers  | 144     | 18.0        | 27              | 8           | Asphalt concrete            |
| 15. | Sokoto  | 255     | 57.3        | 200             | 8           | Asphalt concrete            |

2.2. Data Collection and Description

This study considered secondary sources of data on road pavement surface condition of the selected sites across Nigeria obtained from the database of pavement condition evaluation unit of the present Federal Ministry of Power, Works and Housing Nigeria [3]. The dataset on classified pavement surface condition using the Condition Survey Rating Scores (CSRS) were based on the Average Rut Depth (cm), percentage area of Alligator or Fatigue Cracking per segment and the Drainage condition.

**Average Rut Depth:** it was measured along the wheel path as the depth required to level up the existing pavement surface. It was measured every 20 m when exceeded 3 cm. One measurement for each 100 m was enough when the rutting was not severe (< 3cm). The measurement of rut depth was done using a long straight edge laid across the wheel path. Figure 1 presents pavement rutting and how to measure severity levels.

![Figure 1. Pavement Rutting (a) Sample of Rutting (b) Measurement of Severity Level.](image)
Table 2. Level of Severity of Rut Depth Classification

| Level of Severity | Rut Depth (cm) |
|-------------------|----------------|
| None              | 0 – 1          |
| Slight            | 1 – 2          |
| Moderate          | 2 – 3          |
| Severe            | > 3            |

Alligator or Fatigue Cracking: it was measured and recorded using the AASHO T-274-82 Road Test procedure. The cracking was divided into Class I, Class II and Class III. The AASHO Class I cracking was defined as longitudinal cracks in the wheel path which were generally wavy and in places they crossed and crisscrossed. They were usually numerous separate cracks of 2 – 3m length rather than one single long crack. The AASHO Class II cracking were those that had progressed and interconnected to form chicken wire or alligator skin pattern with numerous small paragon and octagon shapes pieces. At this stage, the pieces were still together and disintegration had not begun. The AASHO Class III cracking were the progression of Class II where cracks were spalled more separately at the edges, the small pieces lost integrity between the blocks, and the segments of the pavement surface loosen, moved or rock under traffic. Some pieces may have moved apart or miss out. Figure 2 presents a typical view of alligator cracks.

Figure 2. Alligator Cracks

The percentage area of total cracking for each class per road segment was then computed using Equation (3):

\[
\text{Density of Section (\%) = \frac{\text{Total Affected Area Per Section}}{\text{Total Area of Road Section}}} \times 100 - - - (3)
\]

The severity levels were classified using the scale shown in Table 3:

Table 3. Level of Severity of AASHO Classification of Cracks [3]

| AASHO Classes | Level of Severity | Density of Section Area (%) |
|---------------|-------------------|-----------------------------|
| None          | None              | 1 – 10                      |
| Class I       | Slight            | 11 – 26                     |
| Class II      | Moderate          | 26 – 50                     |
| Class III     | Severe            | > 50                        |

Drainage condition: this was classified based on the following descriptions;

Very Good: a drainage section characterised with well drained side slopes, high embankments and good runoff ditches.
**Good:** a drainage section characterised with moderate side slopes and ditches, and water probably runs off reasonably well to the surrounding streams and rivers.

**Adequate:** this drainage condition is characterised with some side slope and ditches of moderate size, however, there are evidence that the rate of water runoff is less than desired and some water stand along the roadway. The roadway section may be close to level with the surrounding terrain.

**Poor:** this is when the drainage is characterised with very little side slope and poor ditches. It may be slightly lower than the surrounding terrain; water probably stands and the rate of runoff is very slow.

**Very Poor:** this is a bathtub type of section which is clearly lower than the surrounding terrain. Some side slopes and ditches may be present, but the water is not expected to be carried away and most likely collects and slowly percolates into the sub-base and subgrade surrounding soils of the section.

The classification of CSRS employed the scale presented in Table 4;

| Classification of Pavement Condition | Limits of CSRS |
|--------------------------------------|----------------|
| Excellent                            | > 81           |
| Good                                 | 66 - 81        |
| Fair                                 | 46 – 65        |
| Poor                                 | 25 – 45        |
| Very poor                            | < 25           |

2.3. Implementation of Naïve Bayes Theorem using WEKA Software
This involved using Naïve Bayes classification algorithms or classifier of WEKA software. It required data preparation in Microsoft Excel worksheet in form of column-separated value (.csv) file which was imported into WEKA explorer as an Attribute-Relation File Format (ARFF). The test or observed data file saved in column-separated value (.csv) file format contained values for the independent attributes responsible for pavement condition which included percentage creaking, rut depth and drainage condition entered in the spreadsheet with rows representing instances, columns for attributes per segment for the classification of initial pavement condition as the dependent (target) attribute on a Condition Survey Rating Scores (CSRS) scale translated into Excellent, Good, Fair, Poor and Very Poor according to thresholds proposed by the study. The output of analysis using WEKA software presents confusion matrices with perfect diagonal to fit the targeted attributes into classes, while erroneous classifications were caused by incorrect classification which were estimated using statistical errors.

3. Results and Discussion
The distribution of classified flexible road pavement surface condition of the investigated Federal Highway links in Nigeria using Naïve Bayes classifier is as presented in Figure 3;
Figure 3 presents confusion matrices of classifications based on attributes into Excellent, Good, Fair, Poor and Very Poor as the case may be. The matrices showed the certainty or accuracy of classifications based on the diagonal entries, where a perfect diagonal matrix as shown in Figures 3 (h) and (n) depicted perfect road pavement surface condition classification, while classifications in Figures 3 (a), (b), (c), (d), (e), (f), (g), (i), (j), (k), (l), (m) and (o) showed erroneous classifications indicated by the dispersed entries outside the diagonal forming the upper and lower triangles of the matrices. The imperfect classifications were attributed to missing or incomplete data and noisy or outlier entries in the dataset [5][43]. The numerical performance of the model was also evaluated using Figures 4;
Figure 4 revealed the correctness of classifications by the Naïve Bayes model, where each classified link had over 90% correctly classified instances except links 89, 716, 17 and 138 in Anambra, Borno, Ogun and Plateau states respectively. This was attributed to the significant deviation of pattern of attributes caused by missing and noisy elements in the dataset [5][52]. The classification was further verified using estimated errors by the model as shown in Figure 5;
Figure 5 revealed that the computed Root Relative Square Error (RRSE) for links 89, 716, 17 and 138 in Anambra, Borno, Ogun and Plateau states respectively were relatively high compared to the other sampled links, with corresponding increase in the estimated Relative Absolute Error (RAE). The systematic increase in RRSE justified the relationship between individual entries on a sampled link, while the RAE defined abnormalities in the data entry [39][43][64]. Other strong statistical variable used for measuring the degree of accuracy was the Kappa statistics, which measures between 0 – 1 for least to high accuracy respectively. Figure 6 presents the distribution of Kappa statistics of the sampled links.
Figure 6. Accuracy of Classifications

Figure 6 revealed that surface condition classifications for links 375, 8 and 144 had relatively high degree of accuracy as compared to links 89, 716, 17 and 138. This trend agreed with the earlier assertion that, missing data and noise elements in the dataset had affected the accuracy of some classification significantly. The analysis of link statuses which grouped classified links as Excellent and Good into ‘Worthy’ and Fair, Poor an Very Poor into ‘Unworthy’ statuses indicated that the entire road surface conditions is described using Figure 7;
Figure 7 showed that links 716, 5, 8, 22 and 136 in Borno, Kwara, Lagos, Oyo and Plateau states respectively had relatively high level of unworthiness for surface condition, which increases safety risk, vehicle wear and level of pollution, hence call for urgent repair actions. On the other hand, links 89, 375, 370, 130, 17, 332, 138, 144 and 255 for Anambra, Bendel, Imo, Kaduna, Ogun, Plateau, Rivers and Sokoto states respectively had worthy surface condition, were safe for driving and do not required major maintenance process as at the time of the field investigation.

4. Conclusion
The study carried out surface condition classification of flexible road pavement using the Naïve Bayes classifier. Surface condition attributes used for the classification included, percentage of fatigue cracks, average rut depth and drainage condition to estimate the Condition Survey Rating Scale (CSRS) of the road pavement segments. Fifteen (15) Federal Highway links across Nigeria were considered for the analysis. The high sensitivity of Naïve Bayes classifier yielded high degree of classification accuracy. Results of the analysis indicated that; links 716, 5, 8, 22 and 136 in Borno, Kwara, Lagos, Oyo and Plateau states respectively had relatively high level of unworthy surface condition for safe travel, which also increased risk and cost of plying the highways, hence call for immediate maintenance and rehabilitations actions. While links 89, 375, 370, 130, 17, 332, 138, 144 and 255 from Anambra, Bendel, Imo, Kaduna, Ogun, Plateau, Rivers and Sokoto states respectively had worthy surface condition for safe driving and do not required immediate maintenance services as at the time of the field survey.

References
[1]. Mallick R B and El-Korchi T 2009 Pavement engineering principles and practice, Taylor and Francis Group, USA.
[2]. Taylor M A P and Philip M L 2015 Investigating the impact of maintenance regimes on the design life of road pavements in a changing climate and the implications for transport policy. Transp. Policy, 41, pp 117 – 35.
[3]. Claros G, Carmichael R F and Harvey J 1986 Development of pavement evaluation unit and rehabilitation procedure for overlay design method. Lagos: Texas research and development foundation for the Nigeria Federal Ministry of Works and Housing, Nigeria.

[4]. Fwa T F, Tan C Y and Chan W T 1994 Road-maintenance planning using genetic algorithms II: analysis, J. of Transp. Eng., 120(5), pp 710 – 22.

[5]. Inkoom S, Sobanjo J, Barbu A and Niu X 2019 Pavement crack rating using machine learning frameworks: partitioning, bootstrap forest, boosted tree, Naïve Bayes, and K-Nearest neighbors, J. of Transp. Eng., Part B: Pavement, 145(3), pp 1 – 12.

[6]. Prozzi J A 2001 Modeling Pavement performance by combining field and experimental data, PhD Thesis at Civil and Environmental Engineering, University of California Berkeley, USA.

[7]. Jeong H, Kim H, Kim K and Kim H 2017 Prediction of flexible pavement deterioration in relation to climate change using fuzzy logic. J. of Infrastructure System, American Society of Civil Engineers (ASCE), 23(4), pp 1 - 11.

[8]. Alharbi F 2018 Predicting pavement performance utilizing Artificial Neural Network (ANN) Models, PhD Thesis, Iowa State University capstones, Iowa, Ames, USA.

[9]. Najafi S 2015 Pavement Friction Management (PFM) – A step towards zero fatalities, PhD thesis, Faculty of the Virginia Polytechnic Institute and State University, Virginia, USA.

[10]. Kirbas U and Karasahin M 2016 Performance models of hot mix asphalt pavement in urban roads, Const. and Build. Materials, 116, pp 281 – 88.

[11]. Adeke P T, Atoo A A and Joel E 2018a A policy framework for efficient and sustainable road transport system to boost synergy between urban and rural settlements in developing countries: a case of Nigeria, 1st International Civil Eng. Conf. (ICEC 2018), Department of Civil Engineering, Federal University of Technology, Minna, Nigeria, 1(1), pp 22 - 30.

[12]. Yin H 2007 Integrating instrumentation data in probabilistic performance prediction of flexible pavement, PhD Thesis in the Department of Civil and Environmental Engineering, Graduate School, the Pennsylvania State University, USA.

[13]. Ayed A 2016 Development of empirical and mechanistic empirical performance models at project and network levels. PhD Thesis, Department of Civil Engineering, University of Waterloo, Canada.

[14]. Ziliute L, Motiejunas A, Kleiziene R, Bribulis G and Kravcovas I 2016 Temperature and moisture variation in pavement structures of the test road, 6th Transport Research Arena, Elsevier, London.

[15]. Murana A A 2016 Characterisation of subgrade materials from some Nigerian sources for use in the Nigeria empirical-mechanistic pavement analysis and design system, PhD Thesis, Department of Civil Engineering, Faculty of Engineering, Ahmadu Bello Univerisy Zaria, Nigeria.

[16]. Pantuso A, Flintsch G W, Katicha S W and Loprecipe G 2019 Development of network-level pavement deterioration curves using the linear empirical Bayes approach, Int. J. of Pavement Eng., pp 1-14

[17]. Marcelino P, Antunes M, de. L, Fortunato E and Gomes M C 2019 Machine learning approach for pavement performance prediction. Int. J. of Pavement Eng., pp 1 – 14.

[18]. Miradi M 2009 Knowledge discovery and pavement performance: intelligent data mining. PhD Thesis submitted to the Section of Road and Railway Engineering, Faculty of Civil Engineering and Geosciences, Delft University of Technology, The Netherlands.

[19]. Abiola O S, Owolabi A O, Odunfa S O and Olusola A 2010 Investigation into causes of premature failure of highway pavements in Nigeria and remedies. In Proc. of the Nigeria Institution of Civil Engineers (NICE) Conference. Abuja, Nigeria.

[20]. Chikezie C U, Olowosulu A T, Abejide O S and Kolo B A 2011 Review of application of genetic algorithms in optimization of flexible pavement maintenance and rehabilitation in Nigeria. World J. of Eng. and Pure and Applied Sc., 1(3), pp 68 – 76.
[21]. Owalabi A and Abiola O S 2011 Development of priority index assessment model for road pavements in Nigeria, 8th Int. Conf. on Managing Pavement Assets, Abeokuta, Nigeria.

[22]. Murana A A, Olowosulu A T and Otuoz H S 2012 Minimum threshold of Monte Carlo cycles for Nigerian empirical-mechanistic pavement analysis and design system. Nigerian J. of Tech, 31(3), pp 321-28.

[23]. TAC 2013 Pavement asset design and management guide, Ottawa; Transport Association of Canada.

[24]. Adefemi B A and Ibrahim A A 2015 Flexible pavement assessment of selected highways in Ifelodun local government, Ikirun-osun, South – Western Nigeria. Int. J. of Eng. and Tech., 5(8), pp 475 – 84.

[25]. Mahmood M S 2015 Network-level maintenance decisions for flexible pavement using a soft computing-based framework. PhD Thesis, Nottingham Trent University, United Kingdom.

[26]. Huang Y 2017 Evaluating pavement response and performance with different simulative tests, PhD Thesis, Virginia Polytechnic Institute and State University, Virginia.

[27]. Saltan M, Terzi S and Kucuksille E U 2011 Backcalculation of pavement layer moduli and Poisson’s ratio using data mining. Expert Systems with Applications, 38, pp 2600–08.

[28]. Martin T C 1996 A review of existing pavement performance relationships. ARRB Transport Research Ltd. Research Report No. 282, Washington, D.C.

[29]. Shekharan A R 1998 Effect of noisy data on pavement performance prediction by artificial neural networks. Transportation Research Record 1643, Washington, D.C., pp 7-13.

[30]. American Society for Testing and Materials (ASTM). 2007 Standard practice for road and parking lots pavement condition index survey. D6433-07. Philadelphia.

[31]. Marianingsih S, Utamingrum F and Bachtiar F A 2019 Road surface types classification using combined of K-Nearest neighbor and Naive Bayes based on GLCM, Int. J. of Advances in Soft Comp. and its Applications, 11(2), pp 15 – 27.

[32]. Adeke P T, Atoo A A and Orga S G 2018b Assessment of pavement condition index: a case of flexible road pavements on the University of Agriculture Makurdi campus. Nigerian J. of Tech. 38(1), pp 15 – 21.

[33]. Pan Y, Zhang X, Cervone G and Yang L 2018 Detection of asphalt pavement potholes and cracks based on the unmanned aerial vehicle multispectral imagery, IEEE J. of Selected Topics in Applied Earth Observations and Remote Sensing, pp 1 – 12.

[34]. Fwa T F and Shamrugam R 1998 Fuzzy logic technique for pavement condition rating and maintenance-needs assessment, 4th Int. Conf. on Managing Pavements, Durban, South Africa, pp. 465 - 476.

[35]. Hamed R I and Kakarash Z A 2016 Evaluate the asphalt pavement performance of rut depth based on intelligent method. Int. J. of Eng. and Comp. Sc., 5(1), pp 15474 – 81.

[36]. Munakata T 2008 Fundamentals of new artificial intelligence, neural evolutionary, fuzzy and more. 2nd Edition, Computer and Information Science Department Cleveland State University, USA.

[37]. Cubero-Fernandez, A., Rodriguez, F. J., Villatoro, R., Olivares, J. and Palomares, J. M. (2017). Efficient pavement crack detection and classification, EURASIP J. on Image and Video Processing, 39, pp 2 -11.

[38]. Russell S J and Norvig P 2010. Artificial Intelligence. A modern Approach. 3rd Edition. Pearson Education, Inc., London.

[39]. Witten I H, Frank E, Hall M A and Pal C J 2016 The WEKA workbench – data mining practical machine learning tools and techniques. 4th edition, Morgan Kaufmann, Elsevier, London.

[40]. Fox C 2018 Data science for transport; self-study guide with computer exercises. Springer Int. Publishing, Switzerland.

[41]. Arifuzzaman M, Gazder U, Alam M S and Sirin O 2019 Modelling of asphalt’s adhesive behaviour using classification and regression tree (cart) analysis. Computational Intelligence and Neuroscience, ID 3183050, Hindawi.
[42]. Smadi O G 2000 Knowledge based expert system pavement management optimisation, paper based on PhD Dissertation, Iowa State University, Ames, Iowa, United States.

[43]. Witten I H and Frank E 2005 Data mining – practical machine learning tools and techniques, 2nd Edition, Morgan Kaufmann, Elsevier, London.

[44]. Gopalakrishnan K, Ceylan H and Attoh-Okine N O 2009 Intelligent and soft computing in infrastructure systems engineering, Recent Advances, Springer, Berlin.

[45]. Gopalakrishnan K, Agrawal A, Ceylan H, Kim S and Choudhary A 2013 Knowledge discovery and data mining in pavement inverse analysis, Transport, 28(1), pp 1-10.

[46]. Bal M 2013 Rough sets theory as symbolic data mining method: an application on complete decision table. Information Science Letters, an Int. J., 2(1), pp 35-47.

[47]. Pawlak, Z. 1982 Rough sets. Int. J. of Computer and Information Sc., 11, pp 341- 3.

[48]. Pawlak, Z. 2002 Rough Sets and Intelligent Data Analysis. Information Sc., 147, pp 1 – 12.

[49]. Mahmood M, Rahman M, Nolle L and Mathavan S 2013 A fuzzy logic approach for pavement section classification. Int. J. of Pavement Research and Tech., Chinese Society of Pavement Engineering, 6(5), pp 620–26.

[50]. Mahmood M, Rahmood M, Mathavan S and Nolle L 2015 Pavement management: data centric rules and uncertainty management in section classification by a fuzzy inference system, Bituminous Mixtures and Pavement, 6, pp 533 – 41.

[51]. Arhin S A, Williams L N, Ribbiso A and Anderson M F 2015 Predicting pavement condition index using international roughness index in a Danse urban area, J. of Civil Eng. Research, 5(1), pp 10 – 17.

[52]. Alam F and Pachauri S 2017 Comparative study of j48, naïve bayes and one-r classification techniques for credit card fraud detection using WEKA, Advances in Computational Sc. and Tech., 10(6), pp 1731 – 43.

[53]. Cigsar B and Unal D 2019 Comparison of data mining classification algorithms determining the default risk, Hindawi Scientific Programming, 2019, ID 8706505.

[54]. Tribhuvan A P, Tribhuvan P P and Gade J G 2015 Applying Naïve Bayesian classifier for predicting performance of a student using WEKA. Advances in Computational Research, 7(1), pp 239 – 42.

[55]. Jang W, Lee J K, Lee J and Han S H 2015 Naïve Bayesian classifier for selecting good/bad projects during the early stage of international construction bidding decisions, Mathematical Problems in Eng., 2015, pp 1 – 12.

[56]. Li, Ningyuan Xie, Wei-chau, Haas, Ralph 1996 reliability– based processing of Markov chains for modeling pavement network deterioration transportation research record: J. of the Transportation Research Board, (1524), Transportation Research Board of the National Academies, Washington, D.C. pp 203–213.

[57]. Rose S, Mathew B S and Isaac K P 2017 Development of probabilistic deterioration models and prioritisation of low volume roads for maintenance, Int. J for Traffic and Transport Eng., 7(2), pp 216 – 31.

[58]. Surendrakuma K, Prashant N and Mayuresh P 2013 Application of Markovian probabilistic process to develop a decision support system for Pavement maintenance management, Int. J. of Sc. and Tech. Research, 2(8), pp 295 – 303.

[59]. Mandiarttha P, Duffield C, Thompson R and Wigan M 2012 A stochastic-based performance prediction model for road network pavement maintenance, Road and Transport Research, ARRB Transport Research Ltd., 21(3), pp 125 – 36.

[60]. Gong H, Sun Y, Shu X and Huang B 2018 Use of random forest regression for predicting IRI of asphalt pavements, Construction and Building Materials, 189, pp 890 – 97.

[61]. Thakur R and Mahajan A R 2015 Pre-processing and classification of data analysis in institutional system using WEKA, Int. J. of Comp. Applications, 112(6), pp 9 – 11.
[62]. Luca M D, Abbondati F, Pirozzi M and Zilioniene D 2016 Preliminary study on runway pavement friction decay using data mining. *6th Transp. Research Area April 18 – 21, 2016. 14*, pp 3751 – 60.

[63]. Sharma T C and Jain M 2013 WEKA Approach for comparative study of classification algorithm. *Int. J. of Adv. Research in Comp. and Communication Eng., 2(4)*, pp 1925 – 1931.

[64]. WEKA 2018 *Waikato Environment for Knowledge Analysis: User’s Manual*, The University of Waikato, New Zealand.

[65]. Hutter F, Kotthoff L and Vanschoren J 2019 *Automated machine learning – methods, systems, challengers*, The Springer series on challengers in machine learning. Springer, Switzerland.

[66]. Federal Government of Nigeria 2012 *Public private partnership manual for Nigeria*, infrastructure concession regulatory commission, Abuja, Nigeria.