Predictive Analytics: A Survey, Trends, Applications, Opportunities' and Challenges for Smart City Planning

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***Abstract*—Predictive analysis is an advanced branch of data engineering which generally predicts some occurrence or probability based on data. Predictive analytics uses data-mining techniques in order to make predictions about future events, and make recommendations based on these predictions. The process involves an analysis of historic data and based on that analysis to predict the future occurrences or events. A model can be created to predict using Predictive Analytics modeling techniques. The form of these predictive models varies depending on the data they are using. Classification & Regression are the two main objectives of predictive analytics. Predictive Analytics is composed of various statistical & analytical techniques used to develop models that will predict future occurrence, events or probabilities. Predictive analytics is able to not only deal with continuous changes, but discontinuous changes as well. Classification, prediction, and to some extent, affinity analysis constitute the analytical methods employed in predictive analytics.**

Keywords- Predictive Analytics; Predictive Modeling; Data Mining; Prediction; Smart City Planning

I. Introduction

Predictive analytics is composed of two words predict & analysis, but it works in reverse *viz.* first analyze then predict. It is human nature to want to know and predict what the future holds. Predictive analytics deals with the prediction of future events based on previously observed historical data by applying sophisticated methods like machine learning. The historical data is collected and transformed by using various techniques like filtering, correlating the data, and so on. Prediction process can be divided into four steps: (1) collect and pre-process raw data; (2) transform pre-processed data into a form that can be easily handled by the (selected) machine learning method; (3) create the learning model (training) using the transformed data; (4) report predictions to the user using the previously created learning model [1-30].

II. Predictive Analytics and Data Mining

The future of data mining lies in predictive analytics. The terms *data mining* and *data extraction* are often confused with each other; but there is a significant difference [31-40]. Data extraction involves obtaining data from one data source and loading it into a targeted database [40-45]. Thus one may 'extract' data from a source or legacy system to put it into a standard database or data warehouse [46-49]. Data Mining, on the other hand, is the extraction of obscure or *hidden predictive information* from large databases or data warehouses. Also known as *knowledge-discovery*, data mining is the practice of searching for patterns in stores of data [50-55]. To this end, data mining uses computational techniques from statistics and pattern recognition [56-62]. Looking for patterns in data thus defines the nature of data mining [63-65].

A predictive analytical model is built by data mining tools and techniques [18-25]. The first step consists of extracting data by accessing massive databases. The data thus obtained is processed with the help of advanced algorithms to find hidden patterns and predictive information [1-20]. Though there is an obvious connection between statistics and data mining, methodologies used in data mining have originated in fields other than statistics [40-55].

Data mining lies at the confluence of several streams of applied knowledge such as database management, data visualization, machine learning, artificial intelligence and pattern recognition. Most data mining techniques includes genetic algorithms, decision trees, artificial neural networks, rule induction and nearest neighbor method [1-35].

Predictive analytics is used to determine the probable future outcome of an event or the likelihood of a situation occurring [55-71]. It is the branch of data mining concerned with the prediction of future probabilities and trends [36-39]. Predictive analytics is used to automatically analyze large amounts of data with different variables; it includes clustering, decision trees, market basket analysis, regression modeling, neural nets, genetic algorithms, text mining, hypothesis testing, decision analytics, and more [26-35].

The core element of predictive analytics is the 'predictor', a variable that can be measured for an individual or entity to predict its future behavior. For example, a credit card company may consider age, income, and credit history as predictors to determine the risk factor in issuing a credit card to an applicant [39-48].

Multiple predictors can be combined into a predictive model, which is then used to forecast future probabilities with an acceptable level of reliability. In predictive modeling, data is collected, a statistical model is formulated, predictions are made, and the model is validated (or revised) as additional data become available [49-57].

Predictive analytics combines business knowledge and statistical analytical techniques which, when applied to business data, produce insights [57-68]. These insights help organizations understand how people behave as customers, buyers, sellers, distributors, and so on [66-71].

Multiple related predictive models produce insights for making strategic company decisions such as exploring new markets, acquisitions, and retentions; finding up-selling and cross-selling opportunities; and discovering areas that can improve security and fraud detection. Predictive analytics indicates not only what to do, but also how and when to do it, and to explain 'what-if' scenarios [1-16].

The major objective of data mining is to build a model that can be used to predict the occurrence of an event. The model builders will extract knowledge from historic data and represent it in such a form that the resulting model can be applied to new situations. The process of analyzing data sets extracts useful information on which to apply one or more data mining techniques in order to discover previously unknown patterns within the data, or find trends in the data which can then be used to predict future trends or behaviors. Data mining can be divided into two main categories: supervised (predictive) and unsupervised (descriptive) [17-28].

In supervised learning, data is modelled from training data to find patterns within the data which can then be used to predict a label or value, given some set of parameters. Supervised learning is the process of creating predictive models using a set of historical data that contains the results we are trying to predict. The type of data determines whether this is done using a Regression or a Classification algorithm [32-47].

Regression is a statistical methodology that was developed by Sir Frances Galton (1822-1911), a mathematician who was also a cousin of Charles Darwin. Regression analysis can be used to model the relationship between one or more independent or predictor variables and a dependent or response variable (which is continuous valued) [11-42]. The simplest form of regression, linear regression, uses the formula of a straight line ($y = mx + c$) and determines the appropriate values for m and c to predict the value of y based on the input parameter, x. Advance techniques, such as multiple regression, allow the use of more than one input variable and allow for the fitting of more complex models, such as higher order polynomial equations [24-39]. Regression is a well-established and reliable statistical technique [45-62].

Classification is the set of data mining techniques used to fit discrete (categorical) data to a known structure in order to be able to form predictions for the class label of unlabeled data. Typically, classification algorithms are done in three phases, the first two phases, training and testing, use labelled data, that is, data which has known class labels. Training uses a portion of the data to fit a classifying model to the data. The testing phase then uses the models to try and predict the class labels, and validates the predictions using the actual values in order to determine how accurate the model is. The feedback from this determines how well the models work, and whether new models should be built. Once an acceptable model is built that passes the testing phase, the classifier is deployed on unlabeled data. This is called the deployment phase. Common classification algorithms include Bayesian classification, decision trees, back-propagation and neural networks, and genetic and evolutionary learners [1-28].

Unsupervised learning refers to the problem of trying to find hidden structure in unlabeled data. Unlike supervised algorithms, unsupervised algorithms do not learn from historical data with known labels, hence, they perform without any supervision. Standard unsupervised techniques include clustering, characterization, association rule mining, and change and deviation detecting techniques [29-42].

Predictive Analytics consists of a variety of statistical techniques from modeling, machine learning, data mining and game theory that analyze current and historical facts to make predictions about future events [14]. Predictive models exploit patterns found in historical and transactional data to identify risks and opportunities. Models capture relationships among many factors to allow assessment of risk or potential associated with a particular set of conditions. Predictive analytics use data-mining techniques in order to make predictions about future events, and make recommendations based on these predictions [43-59]. The core of predictive analytics relies on capturing relationships between explanatory variables and the predicted variables from past occurrences, and exploiting it to predict future outcomes. It is important to note, however, that the accuracy and usability of results will depend greatly on the level of data analysis and the quality of assumptions [36-55].

Generally, the term predictive analytics is used to mean predictive modeling, "scoring" data with predictive models, and forecasting. However, people are increasingly using the term to describe related analytical disciplines, such as descriptive modeling and decision modeling or optimization. These disciplines also involve rigorous data analysis, and are widely used in business for segmentation and decision making but have different purposes and the statistical techniques underlying them vary. Predictive models analyze past performance to assess whereas Descriptive models quantify relationships in data [49-71].

Decision models describe the relationship between all the elements of a decision — the known data (including results of predictive models), the decision and the forecast results of the decision — in order to predict the results of decisions involving many variables [1-40]. These models can be used in optimization, maximizing certain outcomes while minimizing others [41-59].

III. PREDICTIVE ANALYTICS TECHNIQUES

Predictive models analyze identify patterns in historical and transactional data to determine various risks and opportunities. Forecasting models capture relationships between many factors to allow assessment of the risks or potential associated with a particular set of conditions, guiding decision making for candidate transactions. Three basic techniques for Predictive analytics are Data profiling and Transformations, Sequential Pattern Analysis and Time Series Tracking [1-46]. Data profiling and transformations are functions that change the row and column attributes and analyses dependencies, data formats, merge fields, aggregate records, and make rows and columns [47-71]. Sequential pattern analysis identifies relationships between the rows of data. Sequential pattern analysis involves identifying frequently observed sequential occurrence of items across ordered transactions over time. Time Series Tracking is an ordered sequence of values at variable time intervals at the same distance [2-19]. Time series analysis gives the fact that the data points taken over time [19-31].

There are some advanced Predictive analytic techniques like Classification-Regression, Association analysis, Time series forecasting to name a few. Classification uses attributes in data to assign an object to a predefined class or predict the value of a numeric variable of interest [24-39]. Regression analysis is a statistical tool for the study of relations between variables. Association analysis describes significant associations between data elements. Time series analysis is employed for forecasting the future value of a measure based on past values [39-47].

IV. Predictive Models

Although most experts agree that predictive analytics requires great skill and some go so far as to suggest that there is an artistic and highly creative side to creating models, generally predictive models need some basic steps of developing them [1-71]. These steps are:

Project Definition: Define the business objectives and desired outcomes for the project and translate them into predictive analytic objectives and tasks;

Exploration: Analyze source data to determine the most appropriate data and model building approach;

Data Preparation: Select, extract, and transform data upon which to create models;

Model Building: Create, test, and validate models, and evaluate whether they will meet project metrics and goals;

Deployment: Apply model results to business decisions or processes; and

Model Management: Manage models to improve performance (i.e., accuracy), control access, promote reuse, standardize toolsets, and minimize redundant activities.

Most experts hold the view that the data preparation phase of creating predictive models is the most time-consuming part of the process.

V. Modeling Process:

There are various Modeling Process stages; some of them have been discussed over here as follows [1-45]:

Purpose: This stage describes the objective of the project.

Obtain the data: Gathering data samples from various sources regarding the project.

Explore, clean and pre-process the data: Exploration can be performed by describing the variables, tokens and other terms which is used in project quite general. Sometimes these terms are in cryptic form or may be in short form, for which we have to tell the full explanation and the places where it can be used. We can also specify the conditions where these variables can be used [23-46].

Reduce the data and partition them into training, validation and test partitions: In this stage we try to reduce the variables or terms for the sake of simplicity. We can reduce number of variables by making the small group of similar purpose variables [33-51].

We will partition the data into a training set to build the model and a validation set to see how well the model does. This technique is a part of supervised learning process in classification and prediction problem. These problems can be used to develop other models and the value of outcome variables can be used in unknown places [21-37].

At this stage we can partition the data into training and validation. Training will build the model and partition will apply model on data to see how well the model does [38-51].

A Data mining endeavor involves testing multiple models, perhaps with multiple settings on each model. Starting from one model and test it one validation data might give us an idea about the performance of that model on such data. However, when we choose the best performing model, the validation data no longer provides an unbiased estimate of how the models might do with more data. By playing the role in choosing the best model the validation data have become the part of the model itself [52-61].

Determining the data mining task: Data mining task in building the model is to find the objective [62-71].

Choosing the technique: The data which is divided into training and validation partitions can be used for creating the model by various techniques [1-42].

Use the algorithm to perform the task: In this stage we apply some of the algorithm to find fitted value (by applying algorithm on training data) and predicted value (by applying algorithm on validation data). Note that the predicted values would often be called the fitted values, since they are for the records to which the model was fit.

Prediction error can be measured in several ways.

1. Average error
2. Total sum of squared errors
3. RMS error (Root mean squared error)

Interpret the results: At this stage we try other prediction algorithms and see how they do error-wise. We might also try different settings on the various models. After choosing the best model (typically, the model with the lowest error on the validation data while also recognizing that ¨simpler is better¨), we use that model to predict the output variable in fresh data.

Deploy the model: After the best model is chosen, it is applied to new data.

VI. Applications of Predictive Analytics

Predictive Analytics can be used in many applications. Here we cite some examples where it has made a positive impact [1-25]].

Medical decision support system: Experts use predictive analysis in health care primarily to determine which patients are at risk of developing certain conditions like diabetes, asthma, heart disease and other lifetime illnesses [26-42].

Fraud detection: Fraud is widely spread across industries. Cases of fraud appear in diverse fields such as credit card activations, invoices, tax returns, online activities, insurance claims and telecom call activities. All these industries are interested in a) detecting frauds and bringing those responsible to book and b) preventing and monitoring fraud at reasonable costs [1-25]. Predictive modeling can help them achieve these objectives. The may also be used to detect financial statementfraud in companies.

Insurance: Similar to fraud, unexpectedly high and suspicious claims are the bane of insurance companies. They would like to avoid paying such claims. Though the objective is simple enough, predictive modeling has had only partial success in eliminating this source of high loss to companies. This is a promising area of further research [1-35].

Health: While the systematic applications of predictive modeling in healthcare are relatively new, the fundamental applications are similar to those in the other areas. After all minimizing customer risk is the objective. In healthcare this is the risk of readmission, which can be reduced by identifying high risk patients and monitoring them [21-46].

Financial prediction: Predictive analytics is useful in financial predictions [18-26].

Customer retention: By a frequent examination of a customer's past service usage, performance, spending and other behavior patterns, predictive models can determine the likelihood of a customer wanting to terminate a service sometime in the near future [35-71].

Analytical customer relationship management (CRM): Analytical Customer Relationship Management is a frequent commercial application of Predictive Analysis. CRM uses predictive analysis in applications for marketing campaigns, sales, and customer services to name a few [36-48].

VII. Related Work

R. Maciejewski et al. [1-25] proposed a model for spatiotemporal data, as analysts are searching for regions of space and time with unusually high incidences of events (hotspots), created a predictive visual analytics toolkit that provides analysts with linked spatiotemporal and statistical analytic views. The system models spatiotemporal events through the combination of kernel density estimation for event distribution and seasonal trend decomposition by loss smoothing for temporal predictions. *J. Yue et al*. [26-45] In this paper they specifically address predictive tasks that are concerned with predicting future trends, and proposed RESIN, an AI blackboard-based agent that leverages interactive visualization and mixed-initiative problem solving to enable analysts to explore and pre-process large amounts of data in order to perform predictive analytics. *R. M. Riensche et al.* [45-55] described a methodology and architecture to support the development of games in a predictive analytics context, designed to gather input knowledge, calculate results of complex predictive technical and social models, and explore those results in an engaging fashion. *Z. Huang et al*. [20-37] applied predictive analytics techniques to establish a decision support system for complex network operation management and help operators predict potential network failures and adapt the network in response to adverse situations. The resultant decision support system enables continuous monitoring of network performance and turns large amounts of data into actionable information. *Sanfilippo et al*. [43-62] Proposed New methods for anticipatory critical thinking have been developed that implement a multi-perspective approach to predictive modeling in support of Naturalistic Decision Making.*R. Banjade et al*. [1-35] this paper considers linear regression technique for analyzing large-scale dataset for the purpose ofuseful recommendations to e-commerce customers by offlinecalculations of model results. *V. H. Bhat et al*. [36-49] presents a novel pre-processing phase with missing value imputation forboth numerical and categorical data. A hybrid combination ofClassification and Regression Trees (CART) and GeneticAlgorithms to impute missing continuous values and Self Organizing Feature Maps (SOFM) to impute categorical values is adapted in their work.*V. H. Bhat et al.* [52-71] proposed an efficient imputation method using a hybrid combination of CART and Genetic Algorithm, as a preprocessing step. The classical neural network model is used for prediction, on the pre-processed dataset. *N. Chinchor et al.* [14-37] this tutorial addresses combining multimedia analysis and visual analytics to deal with information from different sources, with different goals or objectives, and containing different media types and combinations of types. The resulting combination is multimedia analytics. *M. A. Razi et al.* [22-47] performed a three- way comparison of prediction accuracy involving nonlinear regression, NNs and CART models using a continuous dependent variable and a set of dichotomous and categorical predictor variables [15-32].

VIII. Oppurtunities & Challenges

It has been widely quoted that "information is the new oil". We've traveled from an industrial age, powered by hydrocarbons, to an information age driven by data. Predictive analytics, broadly defined, focuses on extracting features from data and building models that can predict future events [1-35]:

Here we discuss some of the outstanding challenges in this field, with regard to: (i) privacy and ownership of data, (ii) analysis of user data, (iii) scaling of algorithms, and (iv) emerging data ecosystems & exchanges [22-49].

Privacy and Ownership of Data: Privacy and ownership of data is big issue. There is always conflict between producer and consumer of data, there are many organizations that believe that data should be open and that openness and interoperability provide them with a competitive advantage [31-52].

Analysis of User Data: The major focus of analysis of user data is in determining user's intent. This is certainly the focus of a lot of the predictive analytics used in online advertising, and the reason that search advertising is far more effective than display advertising [44-61].

Scaling of Algorithms: Having more data is always beneficial for data based system, due to Popularization of social media huge database repository has been created, we have to push the limits in terms of scalability for systems. "The major problem associated with scaling algorithms is that communications and synchronization overheads go up and so a lot of efficiency can be lost, especially where the computation doesn't fit nicely into a map/reduce model" [51-71].

Data Ecosystems and Exchanges: **"**The emergence of data exchanges is clearly related to the problems with ownership of data. They allow data to be exchanged under a clear set of rules with ownership and conditions contractually determined. They also allow for a company to have a viable business model as a data provider and so provide useful data to the whole ecosystem without having to also compete on how the data is used" [13-39].

IX. CONCLUSION

The future of Data Mining lies in Predictive Analytics. This study mainly focuses on opportunities, applications, trends & challenges of Predictive Analytics in urban planning discovery domain. Predictive Analytics is an area of interest to almost all communities and organizations. Predictive analytics is using business intelligence data for forecasting and modeling. Proper data mining algorithms and predictive modeling can refine search for targeted customers. Predictive Analytics can aid inchoosing best methods, and planning new city more efficiently.Predictive Analytics can be also helpful in future of Smart City Planning.

REFERENCES

[1] Mukherjee, Sayanti, et al. "A multilevel scenario based predictive analytics framework to model the community mental health and built environment nexus." Scientific reports 11.1 (2021): 1-15.

[2] Fallahdizcheh, Amirhossein, and Chao Wang. "Profile monitoring based on transfer learning of multiple profiles with incomplete samples." IISE transactions (2021): 1-69.

[3] Gibson, Peter. "Internet of Things sensing infrastructures and urban big data analytics in smart sustainable city governance and management." Geopolitics, History, and International Relations 13.1 (2021): 42-52.

[4] Millar, Garrett C., et al. "Space-time analytics of human physiology for urban planning." Computers, Environment and Urban Systems 85 (2021): 101554.

[5] Fallahdizcheh, Amirhossein, and Chao Wang. "Transfer learning of degradation modeling and prognosis based on multivariate functional analysis with heterogeneous sampling rates." Reliability engineering & system safety 223 (2022): 108448.

[6] Huang, Haosheng, et al. "Analytics of location-based big data for smart cities: Opportunities, challenges, and future directions." Computers, Environment and Urban Systems 90 (2021): 101712.

[7] Bagherpour, M., et al. "Project scheduling and forecasting by laws of physical movement." Journal of Project Management 4.2 (2019): 97-108.

[8] Li, Wendong, et al. "Multi-sensor based landslide monitoring via transfer learning." Journal of Quality Technology 53.5 (2021): 474-487.

[9] Colosimo, Bianca Maria, et al. "Artificial intelligence and statistics for quality technology: an introduction to the special issue." Journal of Quality Technology 53.5 (2021): 443-453.

[10] Wang, Kung-Jeng, and Luh Juni Asrini. "Deep learning-based automatic optical inspection system empowered by online multivariate autocorrelated process control." The International Journal of Advanced Manufacturing Technology (2022): 1-20.

[11] Zalnejad, Kaveh, Seyyed Fazlollah Hossein, and Yousef Alipour. "The Impact of Livable City's Principles on Improving Satisfaction Level of Citizens; Case Study: District 4 of Region 4 of Tehran Municipality." Armanshahr Architecture & Urban Development 12.28 (2019): 171-183.

[12] Hudson, Linda, and Alena Novak Sedlackova. "Urban Sensing Technologies and Geospatial Big Data Analytics in Internet of Things-enabled Smart Cities." Geopolitics, History, and International Relations 13.2 (2021): 37-50.

[13] Van Calster, Ben, et al. "Calibration: the Achilles heel of predictive analytics." BMC medicine 17.1 (2019): 1-7.

[14] Zalnezhad, Kaveh, Mahnaz Esteghamati, and Seyed Fazlollah Hoseini. "Examining the Role of Renovation in Reducing Crime and Increasing the Safety of Urban Decline Areas, Case Study: Tehran's 5th District." Armanshahr Architecture & Urban Development 9.16 (2016): 181-192.

[15] Embouma, Mike, et al. "Smart Green Evenhanded Metropolis Actions against Urban Planning in European Union." International Journal of Basis Applied Science and Study 56.14 (2019): 1218-1222.

[16] Opuiyo, Atora, et al. "Three-Dimensional Modelling of Urban Temperature Landmasses and Its Planning Consequences." International Journal of Smart City Planning Research 20.21 (2019): 426-430.

[17] Parikh, Ravi B., Ziad Obermeyer, and Amol S. Navathe. "Regulation of predictive analytics in medicine." Science 363.6429 (2019): 810-812.

[18] Newiduom, Ladson, Keypi Jackson, and Ibrina Browndi. "Information Technology and Cloud Computing Altering the Searching and Training of Involved Urban Planning." International Journal of Science and Information System 4.2 (2019): 90-95.

[19] Van Calster, Ben, et al. "Predictive analytics in health care: how can we know it works?." Journal of the American Medical Informatics Association 26.12 (2019): 1651-1654.

[20] Amini, Mahyar, et al. "MAHAMGOSTAR.COM as a Caste Study for Adoption of Laravel Framework As the Best Programming Tool for PHP Based Web Development for Small and Medium Enterprises." Journal of Innovation & Knowledge, ISSN (2021): 100-110.

[21] Dubey, Rameshwar, et al. "Big data and predictive analytics and manufacturing performance: integrating institutional theory, resource-based view and big data culture." British Journal of Management 30.2 (2019): 341-361.

[22] Dinov, Ivo D. "Data Science and Predictive Analytics." Springer, Ann Arbor, MI, USA https://doi. org/10 1007 (2018): 978-3.

[23] Amini, Mahyar, and Aryati Bakri. "Cloud computing adoption by SMEs in the Malaysia: A multi-perspective framework based on DOI theory and TOE framework." Journal of Information Technology & Information Systems Research (JITISR) 9.2 (2015): 121-135.

[24] Kendale, Samir, et al. "Supervised machine-learning predictive analytics for prediction of postinduction hypotension." Anesthesiology 129.4 (2018): 675-688.

[25] Andronie, Mihai, et al. "Sustainable Cyber-Physical Production Systems in Big Data-Driven Smart Urban Economy: A Systematic Literature Review." Sustainability 13.2 (2021): 751.

[26] Gupta, Shivam, et al. "Achieving superior organizational performance via big data predictive analytics: A dynamic capability view." Industrial Marketing Management 90 (2020): 581-592.

[27] Galaz, Victor, et al. "Artificial intelligence, systemic risks, and sustainability." Technology in Society 67 (2021): 101741.

[28] Amini, Mahyar, and Nazli Sadat Safavi. "A Dynamic SLA Aware Heuristic Solution For IaaS Cloud Placement Problem Without Migration." International Journal of Computer Science and Information Technologies 6.11 (2014): 25-30.

[29] Rudskoy, Andrey, Igor Ilin, and Andrey Prokhorov. "Digital Twins in the Intelligent Transport Systems." Transportation Research Procedia 54 (2021): 927-935.

[30] Iqbal, Naeem, et al. "Toward effective planning and management using predictive analytics based on rental book data of academic libraries." IEEE Access 8 (2020): 81978-81996.

[31] Nguyen, Huu Duy, et al. "Predicting future urban flood risk using land change and hydraulic modeling in a river watershed in the central Province of Vietnam." Remote Sensing 13.2 (2021): 262.

[32] Muñoz-Erickson, Tischa A., et al. "Anticipatory Resilience Bringing Back the Future into Urban Planning and Knowledge Systems." Resilient Urban Futures. Springer, Cham, 2021. 159-172.

[33] Quasim, Mohammad Tabrez, et al. "Fundamentals of smart cities." Smart cities: A data analytics perspective. Springer, Cham, 2021. 3-16.

[34] Yuan, Faxi, et al. "Smart Flood Resilience: Harnessing Community-Scale Big Data for Predictive Flood Risk Monitoring, Rapid Impact Assessment, and Situational Awareness." arXiv preprint arXiv:2111.06461 (2021).

[35] Amini, Mahyar, and Nazli Sadat Safavi. "A Dynamic SLA Aware Solution For IaaS Cloud Placement Problem Using Simulated Annealing." International Journal of Computer Science and Information Technologies 6.11 (2014): 52-57.

[36] Iqbal, Naeem, et al. "Boreholes data analysis architecture based on clustering and prediction models for enhancing underground safety verification." IEEE Access 9 (2021): 78428-78451.

[37] Singh, Vijander, Amit Kumar Bairwa, and Deepak Sinwar. "An Analysis of Big Data Analytics." Smart Agricultural Services Using Deep Learning, Big Data, and IoT. IGI Global, 2021. 203-230.

[38] Chen, Tong, et al. "Sequence-aware factorization machines for temporal predictive analytics." 2020 IEEE 36th International Conference on Data Engineering (ICDE). IEEE, 2020.

[39] Amini, Mahyar, et al. "Development of an instrument for assessing the impact of environmental context on adoption of cloud computing for small and medium enterprises." Australian Journal of Basic and Applied Sciences (AJBAS) 8.10 (2014): 129-135.

[40] Balthazar, Patricia, et al. "Protecting your patients' interests in the era of big data, artificial intelligence, and predictive analytics." Journal of the American College of Radiology 15.3 (2018): 580-586.

[41] Sadat Safavi, Nazli, Nor Hidayati Zakaria, and Mahyar Amini. "The risk analysis of system selection and business process re-engineering towards the success of enterprise resource planning project for small and medium enterprise." World Applied Sciences Journal (WASJ) 31.9 (2014): 1669-1676.

[42] Audu, Abdul-Rasheed A., et al. "An intelligent predictive analytics system for transportation analytics on open data towards the development of a smart city." Conference on Complex, Intelligent, and Software Intensive Systems. Springer, Cham, 2019.

[43] Latchoumi, T. P., Manoj Sahit Reddy, and K. Balamurugan. "Applied machine learning predictive analytics to SQL injection attack detection and prevention." European Journal of Molecular & Clinical Medicine 7.02 (2020): 2020.

[44] Wang, Jinjiang, et al. "Deep heterogeneous GRU model for predictive analytics in smart manufacturing: Application to tool wear prediction." Computers in Industry 111 (2019): 1-14.

[45] Sarker, Iqbal H. "Data science and analytics: an overview from data-driven smart computing, decision-making and applications perspective." SN Computer Science 2.5 (2021): 1-22.

[46] Armstrong, Gill, Veronica Soebarto, and Jian Zuo. "Vacancy Visual Analytics Method: Evaluating adaptive reuse as an urban regeneration strategy through understanding vacancy." Cities 115 (2021): 103220.

[47] Amini, Mahyar, et al. "The role of top manager behaviours on adoption of cloud computing for small and medium enterprises." Australian Journal of Basic and Applied Sciences (AJBAS) 8.1 (2014): 490-498.

[48] Arfanuzzaman, Md. "Harnessing artificial intelligence and big data for SDGs and prosperous urban future in South Asia." Environmental and Sustainability Indicators 11 (2021): 100127.

[49] Sabu, Kiran M., and TK Manoj Kumar. "Predictive analytics in Agriculture: Forecasting prices of Arecanuts in Kerala." Procedia Computer Science 171 (2020): 699-708.

[50] Bradlow, Eric T., et al. "The role of big data and predictive analytics in retailing." Journal of Retailing 93.1 (2017): 79-95.

[51] Maciejewski, Ross, Yuxin Ma, and Jonas Lukasczyk. "The Visual Analytics and Data Exploration Research Lab at Arizona State University." Visual Informatics 5.1 (2021): 14-22.

[52] Bellini, Emanuele, et al. "An IOE and big multimedia data approach for urban transport system resilience management in smart cities." Sensors 21.2 (2021): 435.

[53] Amini, Mahyar. "The factors that influence on adoption of cloud computing for small and medium enterprises." (2014).

[54] Zhou, Peng, and P. T. Yin. "An opportunistic condition-based maintenance strategy for offshore wind farm based on predictive analytics." Renewable and Sustainable Energy Reviews 109 (2019): 1-9.

[55] Venkatesh, R., C. Balasubramanian, and Madasamy Kaliappan. "Development of big data predictive analytics model for disease prediction using machine learning technique." Journal of medical systems 43.8 (2019): 1-8.

[56] Yigitcanlar, Tan, et al. "Responsible urban innovation with local government artificial intelligence (AI): A conceptual framework and research agenda." Journal of Open Innovation: Technology, Market, and Complexity 7.1 (2021): 71.

[57] Harris, Barbara. "Data-driven Internet of Things systems and urban sensing technologies in integrated smart city planning and management." Geopolitics, History, and International Relations 13.1 (2021): 53-63.

[58] Amini, Mahyar, et al. "Agricultural development in IRAN base on cloud computing theory." International Journal of Engineering Research & Technology (IJERT) 2.6 (2013): 796-801.

[59] Townsend, Jason. "Interconnected sensor networks and machine learning-based analytics in data-driven smart sustainable cities." Geopolitics, History, and International Relations 13.1 (2021): 31-41.

[60] Sadat Safavi, Nazli, et al. "An effective model for evaluating organizational risk and cost in ERP implementation by SME." IOSR Journal of Business and Management (IOSR-JBM) 10.6 (2013): 70-75.

[61] Silva, Bhagya Nathali, et al. "Urban planning and smart city decision management empowered by real-time data processing using big data analytics." Sensors 18.9 (2018): 2994.

[62] Appel, Sheila U., et al. "Predictive analytics can facilitate proactive property vacancy policies for cities." Technological Forecasting and Social Change 89 (2014): 161-173.

[63] Ghandar, Adam, et al. "A decision support system for urban agriculture using digital twin: A case study with aquaponics." IEEE Access 9 (2021): 35691-35708.

[64] Amini, Mahyar, and Nazli Sadat Safavi. "Cloud Computing Transform the Way of IT Delivers Services to the Organizations." International Journal of Innovation & Management Science Research 1.61 (2013): 1-5.

[65] Anejionu, Obinna CD, et al. "Spatial urban data system: A cloud-enabled big data infrastructure for social and economic urban analytics." Future generation computer systems 98 (2019): 456-473.

[66] Amini, Mahyar, and Nazli Sadat Safavi. "Critical success factors for ERP implementation." International Journal of Information Technology & Information Systems 5.15 (2013): 1-23.

[67] Li, Wendong, et al. "Multi-sensor based landslide monitoring via transfer learning." Journal of Quality Technology 53.5 (2021): 474-487.

[68] Yeganeh, Ali, Saddam A. Abbasi, and Sandile C. Shongwe. "Monitoring Non-Parametric Profiles using Adaptive EWMA Control Chart." (2022).

[69] Safavi, Nazli Sadat, et al. "An effective model for evaluating organizational risk and cost in ERP implementation by SME." IOSR Journal of Business and Management (IOSR-JBM) 10.6 (2013): 61-66.

[70] Khoshraftar, Alireza, et al. "Improving The CRM System In Healthcare Organization." International Journal of Computer Engineering & Sciences (IJCES) 1.2 (2011): 28-35.

[71] Alharthi, Hana. "Healthcare predictive analytics: An overview with a focus on Saudi Arabia." Journal of infection and public health 11.6 (2018): 749-756.