IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⋇ Impact Factor 7.918 ⋇ Vol. 12, Issue 3, March 2023

DOI: 10.17148/IJARCCE.2023.12301

Developing and Managing the Digital Twin of a Smart City by Using Fuzzy Logic with a Multilayer Perceptron Neural Model (MNM)

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Abstract: With increased technology development, governments and specifically urban managers require the most recent technology to make their smart cities safer. Intelligent transportation systems (ITS) have been highly incorporated within this area to improve effective smart city applications. A digital twin (i.e., a copy of a real-world construct) is required to manage a building structure and resources during smart city construction to optimize the overall perf ormance. This research objective can be achieved by incorporating big data techniques that maximize available resources with the help of a graphical processing unit (GPU) that can manipulate complex data successfully. The GPU integrates fuzzy rough set theory (FRST) and a multilayer perceptron neural model (MNM) to minimize the multi-classification problem during analysis. This neural model uses multiple layers that can understand the data structure and classify resources with minimal computational errors. It uses the AdaBoost learning parameter to minimize complexity while making decisions in smart city applications. This framework uses data from the Internet of Things (IoT) to manage resources and energy in a smart city. The FRST-enabled MNM approach explores the gathered data with appropriate forecasting accuracy while minimizing the running time and computation complexity and increasing the processing speed.

Keywords: Smart City, Intelligent Transportation, Internet of Things (IoT), Big Data, Fuzzy Rough Set Theory, Graphical Processing Unit, AdaBoost.

I. INTRODUCTION

With the development of the Internet of Things (IoT) [1,2], most industries utilize the digital twin (DT) concept because of its ease of use and minimal cost. A smart city is developed via a DT [3] to optimize processes from land use to urban planning. A DT provides the ability to create a simulation plan that exposes issues before development. Digital tools are utilized for architectural planning and analyzing devices, such as wireless network antennas, housing, public transport, and solar panels [4]. For example, the Singapore government is making a continuous, strenuous effort to transfer aspects of the city into a digital format. Therefore, government agencies are constantly analyzing citizens' economic opportunities and communities to maximize citizens' lifestyles [5]. However, only a few countries have begun using this twin city concept; therefore, in 2019, a DT smart city event was conducted. The seminar presented a program to raise awareness about optimized cities and towns. Twin cities have many physical features incorporated into a data-rich digital model. The model is used for waste management, energy consumption, infrastructure management, mobility improvement, security management, and energy consumption [6,7]. These smart city infrastructures are improved via simulated execution with the DT. The developed smart city is economically, environmentally, and socially sustainable and responds to computer-aided design. Twin cities are incorporated with smart maps that help create geospatial analytics [8].

A digital map is utilized to visualize, analyze, and process large, complex data to generate user information. Smart cities have many people; therefore, they must be constructed in a stable and energetic manner with regard to logistics and resources [9,10]. Most cities focus on the public deployment of digital resources, and few applications utilize multi-dimensional data. Hence, the smart city must be constructed to adapt to quantitative and qualitative changes in government's policies. Design changes and the construction process are done with the help of building information modeling (BIM) [11]. This 3D model employs digital computer technology to build complete information about the current situation in a smart city. BIM-based 3D modeling maximizes information integration and provides an effective platform for exchanges regarding decisions [12]. The BIM process includes the use of multimedia technology in the creation of smart city architecture to maximize dynamic performance. The designed digital products are applied to construction displays, reporting, and bidding [13,14].

In addition, BIM techniques are widely used to manage documents, audio and video appreciation, and smart city authenticity. The comprehensive utilization of 3D technologies minimizes problems with inefficiencies, construction

ISO 3297:2007 Certified ⁜ Impact Factor 7.918 ⁜ Vol. 12, Issue 3, March 2023

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risks, and potential design issues in smart city applications and enhances the overall data interpretations. Digital technology is highly incorporated into a DT to improve urban management and service design. The DT collects information from the construction environment with the help of mobile devices, drones, and sensors. Sensor devices, the IoT, and remote communication technologies based on the collected data help design the city's digital copy [15].

In addition, artificial intelligence (AI), big data (BD), machine learning (ML), and cloud computing (CC) enhance digital copy accuracy and data aggregation efficiency. In smart city road traffic, DT cannot virtualize the physical entities' road mapping, but it can dynamically monitor the road infrastructure using network communication and sensor technologies. The DT predicts road events, traffic, and accidents according to traffic conditions and behavior; respective traffic decisions are made to improve smart city performance. Therefore, the present research utilizes the DT concept in smart buildings, urban governance, and medical treatment procedures to enhance these services [17]. The DT was constructed according to BIM techniques to optimize the emergency plan's configurations and resources.

Hence, this research study integrated the BIM and DT concepts to build a smart city to resolve problems, such as security, management, and resource availability. Moreover, the smart city has a large volume of heterogeneous data, which may lead to high data redundancy, untruthfulness, and missing value issues. This research issue is addressed by integrating fuzzy rough set theory (FRST) with a graphical processing unit (GPU) to minimize difficulties in complex data processing. The FRST algorithm works with a multi-perceptron neural model (MNM) to reduce the multi-classification problem during analysis. The MNM categorizes the resources by understanding the data structure, which may decrease computational errors. In addition, the network uses the AdaBoost learning process, which reduces the missing values involved in the data analysis. Therefore, the DT with the BIM model maximizes the data analysis rate with minimal computational complexity.

The research objectives were as follows:

- To improve smart city application performance by incorporating a fuzzy approach, which enhances decision-making.
- To minimize the misclassification problem while analyzing the heterogeneous data in the smart city application.
- To reduce computational complexity and error while investigating the heterogenous data and minimizing false decisions in the smart city application.

The rest of the paper is organized as follows: Section 2 analyzes various researchers' opinions about the DT concept with BIM-based smart city construction. Section 3 discusses the working process of FRST and MNM-based smart city management, and the system's efficiency is evaluated in Section 4. The conclusion is described in Section 5.

II. RELATED WORKS

Xia et al. [18] reviewed and performed a bibliometric analysis of smart city data using DT and BIM techniques. The system uses an ontology data integration approach to investigate the structure of smart city design to improve the overall analysis. During the research, co-country analysis, keyword analysis, coupling analysis, and co-citation analysis were performed using CiteSpace. This process successfully framed the smart city construction design using the BIM and a graphical information system. According to the DT and BIM processes, a smart city's rail transportation was constructed effectively. However, this method encountered high computation consumption difficulties while analyzing the smart city construction requirements.

Azfar et al. [19] constructed a university campus model using a DT simulation. This work intended to visualize the university model while neglecting unwanted information in the application. The research objective was to explore the techniques and tools for identifying resources to improve the campus design. Digital copies were created for buildings, road networks, and terrain and were combined with the CARLA project to enhance the university's traffic simulation and computer vision. This process requires additional effort to enhance the overall modeling of the university.

Wang et al. [20] assessed environmental satisfaction in the DT-based development of buildings using a deep learning approach (DT-DLA). The DLA explored the energy consumption level in BIM to explore the performance of the materials and structural building maintenance. The model was developed by incorporating a data fusion algorithm and a backpropagation neural approach with a dynamic host configuration. This helped in developing an optimized model in the smart city building field, but the optimization techniques require fine-tuning of the network parameters.

ISO 3297:2007 Certified ⁜ Impact Factor 7.918 ⁜ Vol. 12, Issue 3, March 2023

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Alam et al. [21] developed cloud-related cyber-physical systems (CPS) using a DT architecture reference framework. The system aims to resolve CPS's computation, scalability, and cross-domain communication issues. The CPS process's key properties were initially analyzed to construct the DT architecture model. The interaction's degree value was then computed to improve the model's efficiency. In addition, fuzzy rules with a Bayes network (FR-BN) was applied to reconfigure the system efficiency. The created system ensured a minimum latency and maximum efficiency while developing the complex CPS.

Alves de Araujo et al. [22] introduced fuzzy logic (FL) to create a power plant water cooling system using DT (DT-FL). The scheme aimed to manage energy consumption and temperature control while developing a cooling water system. The FL determines the number of fans in the controlling system to reduce over-energy consumption. This process used Brazilian power plant information, and a twin copy of the plant was created and updated according to the fuzzy rules. The fuzzy operation minimized data instability and improved the overall cooling system.

Kumar et al. [23] applied a DT-centric approach to avoid traffic congestion and to predict driver intention. This work was used to optimize resource allocation and utilization connectivity. The twin-centric method provides numerous solutions to traffic-related problems. An ML model and IoT concept were incorporated during this analysis to reduce traffic congestion in 5G communication.

Wang et al. [24] recommended an edge intelligent federation learning (EIFL) approach to process the digital twin's data information for smart cities. This work used a single-shot multiBox detector (SSD) to identify a traffic scene in the traffic system. The algorithm incorporated the residual network to improve overall recognition accuracy. Here, the introduced system utilized the learning process and sigmoid activation function to improve recognition accuracy and training speed. Lv et al. [25] applied computational intelligence techniques in smart city cyber-physical systems to analyze big graphic data. The design was intended to manage data security and privacy using a differential privacy frequent sub-graph big multigraph (DPFS-BM). A differential privacy AlexNet was applied during the analysis to resolve the gradient dispersion problem. The intelligent model utilizes the sigmoid function to explore the output value. The introduced system validated every activity, and the system's efficiency was compared with existing networks, such as a multilayer perceptron, recurrent network, convolution network, and AlexNet. The DPFS-BM approach attained a minimum delay and computation time while analyzing smart city security factors.

Wang et al. [26] applied DTs to manage network slicing with the help of graph neural networks (GNN). This process provides optimal solutions to address network performance cost-effectively. The network environment was continuously observed, and the intertwined relationship was analyzed to manage the network slicing. The GNN approach utilized a non-Euclidean graph structure to understand the network slicing structure that helped control the network environment. The introduced system ensured a minimum latency because of the effective utilization of end-to-end network analysis under various topological conditions. According to various researchers, DTs have been widely utilized in smart city applications to improve performance. However, existing systems fail to manage system efficiency while analyzing heterogeneous data, which causes a computation problem. In the current research, this issue is overcome by applying GPU-integrated fuzzy rough set theory (FRST) and a multi-perceptron neural model (MNM) to minimize the multi-classification problem during the analysis. This process is used to manage the resources and efficiency of a smart city application. The research objectives described earlier were achieved with the help of the fuzzy incorporated neural model and the AdaBoost learning model. The detailed working process is discussed in the following section.

III. FRST AND MNM RESEARCH ANALYSIS IN DT-BASED SMART CITY

The literature analysis clearly states that most smart city applications collect and process data via data mining and ML algorithms. Smart city data are uncertain because it is heterogeneous, leading to redundancy and misclassification problems. Presently, neural models and fuzzy approaches are widely utilized to address uncertainty issues. Therefore, this research used FRST and an MNM to minimize the multi-classification problem during the analysis of smart city applications. These applications use this DT-based data-processing technique to improve performance. An ITS is one of a smart city application's important and core public services. An ITS requires strong information points and comprehensive timelines to maximize its operations and emergency constructions. The ITS utilizes various information technologies and a GPU to maintain transportation connections between resources and traffic simulation users. A traffic monitoring system helps in making decisions, determines resource transmission times, and minimizes traffic congestion. Hence, the smart city application should be constructed with the help of the DT to improve overall performance.

The DT visualizes smart city points; physical connectivity and integrity are maintained to manage the data. The DT framework consists of several components, such as ubiquitous networks, smart terminals, application systems, support

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁞ Impact Factor 7.918 ⁞ Vol. 12, Issue 3, March 2023
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platforms, and run devices (for data collection, integration, aggregation, and analysis). The gathered smart city application data are processed using the FRST and MNM. These techniques are utilized for optimizing the plan and improving smart city construction. The DT-based smart city construction is illustrated in Figure 1.

Generally, smart city construction is incorporated in the cloud with numerous sub-systems to design the emergency and urban command center. Data analysis and big-data techniques have been integrated to reduce government costs and enhance smart city efficiency.

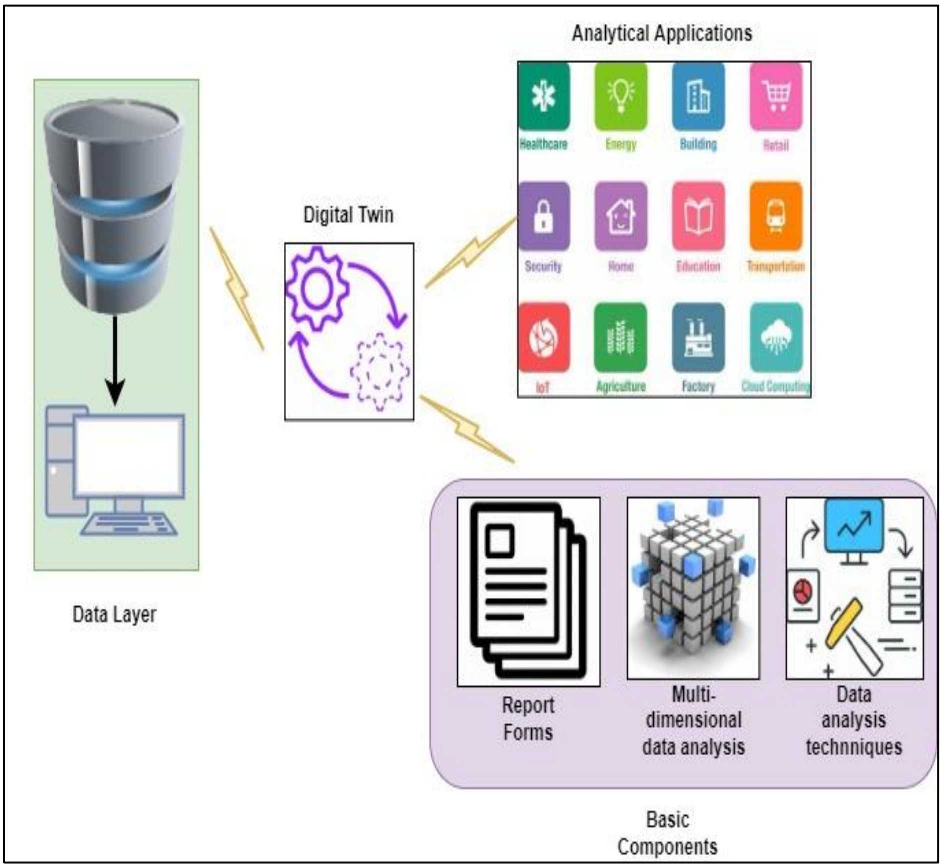

Fig. 1: DT-Based Operating Structure of a Smart City

Figure 1 shows the smart city's main operating component, which includes data layers, analytical applications, and basic components. The smart city utilizes various devices and sensors to collect information stored in the cloud environment. The gathered information is analyzed with the help of these basic components. The basic components consist of multi-dimensional data analytic tools and techniques, such as data mining, BD, and ML techniques. The analysis is performed in various areas, such as health, banking, industry, agriculture, etc.

The analytic component explores each monitored data change with the help of the DT, which minimizes construction difficulties and improves overall smart city performance. The cloud environment is associated with the smart city infrastructure to monitor and collect information. According to the changes in the smart city, cloud services are obtained to observe security, tourism, and overall smart city management.

After collecting information from the location, BIM technology is incorporated to construct the smart city. The BIM technique uses information and collaborative communication to improve city construction. The BIM process creates the city structure by considering all the factors in the digital design. The fundamental characteristics, functions, and physical units are developed and understood from the digital representation. The constructed digital framework is used to understand the city or building knowledge that will help in making effective decisions. These aspects of the BIM lifecycle are illustrated in Figure 2.

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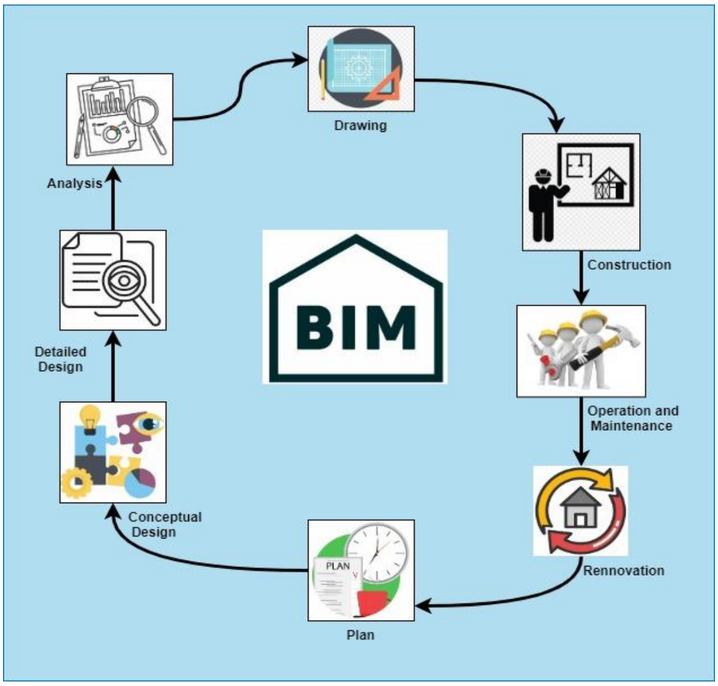

Fig.2: Lifecycle of the BIM Process in a Smart City

The cycle includes several steps: framework drawing, construction, operations and maintenance, renovation, planning, conceptual design, detailed design, and analysis. The lifecycle covers complete information about the smart city, which helps when construction decisions are being considered. In addition, building construction covers the statistical, technical, and economic factors used to build a safe and secure city. The construction process has an animation set that covers almost every camera unit in its three-dimensional design. This architecture understands and visualizes the building structure and the difficulties involved. The BIM model covers the entire urban area, components, and framework details, which are transferred to the next-generation design. In addition, the BIM process derives complete information, including emergency evacuation, illumination analysis, and collision details, via a pretrained program. This BIM data extraction’s main advantage is managing changes to the city with regard to compatibility, programmability, ease of operation, and extensibility.

After this process, the BIM technique generates a model that continuously examines feedback to address problems in the 3D-smart city construction process. The construction staff constantly interacts with the construction unit to verify the model, which helps reduce communication costs and implementation time. The interaction process is enabled with the help of human–computer interaction (HCI), which is integrated with the BIM process to visualize the construction. Computer-aided design and drafting (CAD) is linked with the BIM to draw the constructed model during communication. The CAD process uses an inbuild software package called Autodesk Revit, which helps format the drawing in FBX. The respective identification objects and components are included to implement and optimize the model according to the user interface. Additionally, IoT devices, cameras, and sensor devices are included to improve the representation of the model. Communication is established via local area networks (LANs) and wireless transmission processes, which help in the transmission, analysis, and storage of the data in storage units. During this process, a DT or copy of construction is maintained to reduce construction errors in real-time applications.

Sensor devices collect information from the smart city; this includes several numeric, symbolic, and missing data value sets. Incomplete data lead to reductions in the overall smart city construction efficiency. Therefore, this work utilizes the fuzzy rough approach to identify and model the data to improve overall data processing. The FRST method derives the rules and data without requiring prior knowledge. Moreover, the existing methods have difficulty handling highly dimensional and complex data, which leads to reductions in smart city improvement. These research difficulties are overcome by applying the fuzzy rough set approach, which minimizes the complex data fusion process.

The smart city has an information set with different attributes, called compositive information (CI), $\mathrm{CI} = (\mathrm{UAVf})$. Here, non-empty finite objects are denoted as U; attributes are denoted as A; the value range is defined as V with attribute α, and fused information is denoted as f. The system consists of a decision information system with C condition and D

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decision attributes. Therefore, attribute A is defined as $A = C \cup D$, and the information system in the smart city is defined as $CI = (UC \cup DVf)$. Similarly, the composite information system has decision attributes, condition attributes, and partition attribute B. These attributes are defined within the upper and lower approximation sets of X. These approximation sets are more helpful in decision-making D. The positive side of the decision $POS_{CB}(D)$ is defined from the condition and partition variable decisions, as in the following equation:

$$POS_{CB}(D) = \cup_{j=1}^{m} C_B(D)j \tag{1}$$

The positive impact of the city variables is computed from the CI attribute information, equivalence relation R attributes, compatibility relation T, d neighborhood relations, and K characteristic relations. In the defined information system, the smart city data have a large storage occupation. The data is analyzed with the help of batch processing, which assists in computing the approximation set of the fuzzy rough set. Initially, the relation matrix was developed by using the attributed k-sub matrix. From the sub-matrix, the upper and lower approximate matrices are identified. The GPU is then incorporated to accelerate the approximation set and relation matrices. A decision matrix is developed from the GPU information to improve smart city performance.

The R_B relation matrix is calculated as $R_B = U_B^T \circ U_B$, and it is represented as $\left(r_{ij}\right)_{n*n}$.

This relation matrix is highly incorporated with the upper approximation set of coarse-grained attributes. The fine-grained attributes are never dependent on the relation matrix. The upper approximation of the attribute is then defined as follows:

$$u_{ij} = \vee_{k=1}^{n}\left(r_{ik} \wedge d_{kj}\right) = \vee_{k=1}^{n}\left(\left(x_i \circ x_k\right) \wedge d_{kj}\right) \tag{2}$$

The above-defined process is implemented $T * n$ times to utilize resources effectively. Likewise, the sub-matrix is run $T * m$ times to identify the upper approximation value. The computed values are transmitted to the central processing unit (CPU). According to the approximation set, the decision matrix is developed to identify the data's deviation in the smart city environment. The processed information, structure, and rules are saved in the global memory (GM) to access information from any device. Here, the approximation-related variables are identified with the help of fuzzy logic, which helps to prevent difficulties in variable decision-making. Fuzzy logic has two values, one and zero, which helps to identify the exactness of the variable belonging to a particular region. The fuzzy set has a fuzzification and degree of membership function that determines the exactness of the variable. The fuzzy sets are defined using a trapezoid-shaped curve, which is computed using the sigmoid function $S(x) = \frac{1}{1+e^{-x}}$. According to this function, each variable belonging to the categories is identified to improve decision-making in the smart city applications.

After deciding on a region, the BIM model-based created project should be classified by applying an MNM approach. The MNM technique helps predict each data element, minimizing the misclassification problem while allocating resources. Digital technology provides complete information with lower and upper boundaries that effectively helps to design the present situation. The BIM library has several pieces of information, such as non-component information, geometric details, status information, and professional attributes. This information is incorporated with digital technology, which maximizes the overall performance. The users in the smart city continuously investigate the project construction and analyze the overall improvement. The multi-label classification is performed with the help of the multi-perceptron MNM to minimize the problem during the analysis. The MNM uses multiple layers that understand the data structure and classify the resources with minimal computational error. The neural model uses the AdaBoost learning parameter to minimize complexity while making decisions in the smart city applications.

The MNM approach is one of the feedforward neural models used to investigate IoT-based input data. The network has three layers (input, hidden, and output), which are highly associated with each neuron to compute the output. The network uses supervised learning to predict the exact output of the data. Different data types are presented in the smart city, which are processed by these upper and lower approximation limits to predict the exact problem. The network uses a linear activation function that maps the inputs with the weighted values to predict the output value. Here, the tanh activation function is used to estimate the mapping output. The activation function is defined using the following equation:

$$y(v_i) = \tanh(x_i) \tag{3}$$

The activation function obtains values from -1 to 1, which help to predict the exact data changes in the smart city. The MNM has weight values w_{ij} that are frequently updated to minimize the classification problem. The fine-tuning procedure

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uses a backpropagation learning process, which computes the deviation between the actual and computed output values. The changes in the output are estimated as $e_j(n) = d_j(n) - y_j(n)$; the target output value is denoted as d, and the predicted output value is represented as y. The error rate is then estimated using the following equation:

$$\varepsilon(n) = \frac{1}{2}\sum_j e_j^2(n) \tag{4}$$

After computing the error value, the gradient descent is computed to predict changes in the network weight values, as defined in the following:

$$\Delta w_{ij}(n) = -\eta \frac{\partial \varepsilon(n)}{\partial v_j(n)} y_j(n), \tag{5}$$

where η is denoted as the learning rate, and y is the output value. Weight changes are frequently predicted according to the gradient value, and the fine-tuning procedure is performed. The multi-class classification problem is overcome during the classification process by applying a boosting algorithm. This work uses the AdaBoost learning algorithm to reduce the classification problem. This boosting algorithm is one of the decision tree approaches and can help make successful decisions in smart city construction.

Initially, the dataset was divided into training and testing phases. The training process provides equal weight values to the real data in the smart city. During the training process, the link between the neurons and the inputs is estimated with the help of the weight values and activation function. This computation reduces the weak learning feature involvement to improve the overall classification performance. The boosting algorithm computes the amount of data in the training process, which are investigated according to the network parameters. The boosting algorithm constructs the tree for every iteration to identify the network output value. The label value is utilized to estimate the output value for each input. According to the error value, the network parameters are updated continuously, minimizing the classification problem. The computed outputs help predict the specific data's resources, which minimizes computation difficulties in the smart city environment. The created system efficiency is then evaluated using the respective experimental results and discussion.

IV. RESULTS AND DISCUSSION

This section discusses the efficiency of the BIM approach using the FRST and MNM-based smart city construction. Initially, DT technologies were applied to copy the smart city requirements and construction details. The gathered information was fed into the BIM process to develop the environment while considering user requirements. After that, IoT devices were utilized to collect information and verify the smart city environment improvement.

Here, the collected information was processed by the fuzzy incorporated rough set approach, which analyzes the data in the upper and lower boundary approximations. After that, the data were classified by applying the MNM approach with the AdaBoost learning process to forecast difficulties in the smart city environment. The BIM process was integrated with the GPU to process the user request. Therefore, the GPU's speedup ratio and average running time for different datasets should be investigated. This work used the CityPulse smart city dataset [27] to evaluate the system's efficiency.

The dataset consists of heterogeneous information, including traffic data, pollution, weather, culture, event, library, and parking information. The BIM design must cover this information to implement an effective smart city environment. The dataset consists of 449 observations, which were collected by up to six months of observation. The collected data was processed in the GPU to predict the changes of each data in the smart city construction. The data required resources to complete the task with a minimum running time. The method analyzes each attribute, condition variable, attribute, and decision variable while minimizing the overall running time.

The relation matrix and respective condition variables maximize the data processing speed and reduce the running time. In addition, the GPU runs the smart city information in parallel, minimizing the complexity of the heterogenous data analysis. The GPU process uses a set series calculation that identifies the relationships among the data. The successful utilization of BIM planning strategies and DT procedures reduces data destruction and improves overall data processing speed. The graphical analysis of the speedup is illustrated in Figure 3.

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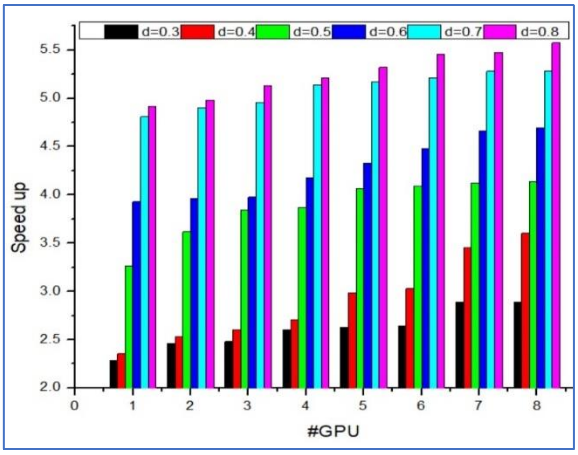
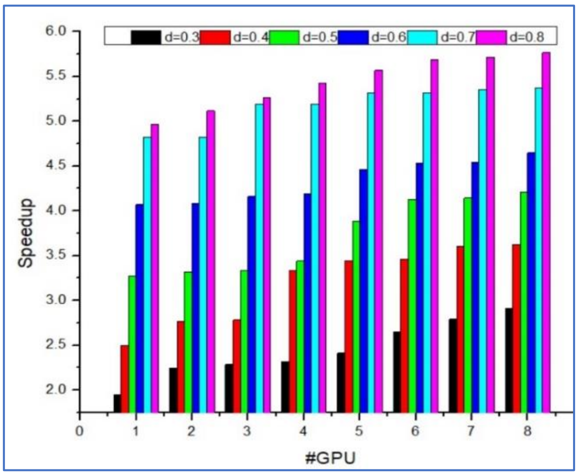
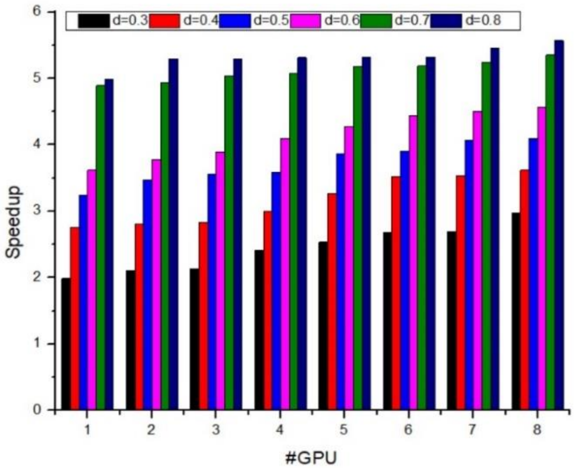


(a) Dataset 1



(b) Dataset 2



(c) Dataset 3

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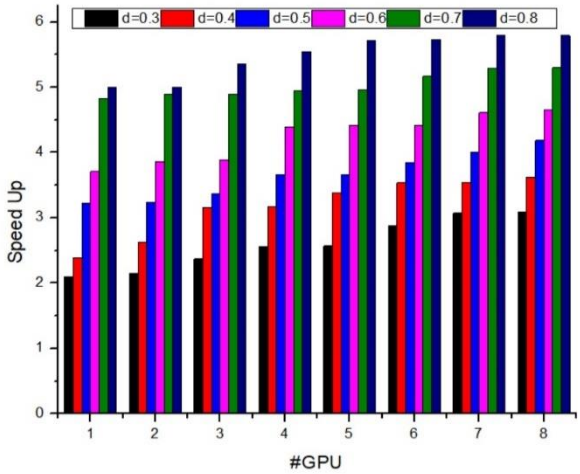
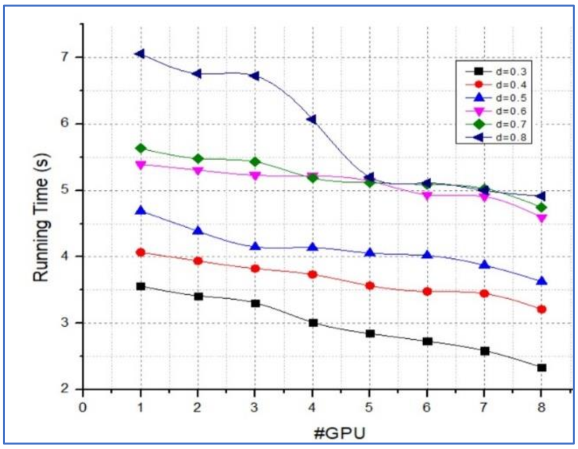


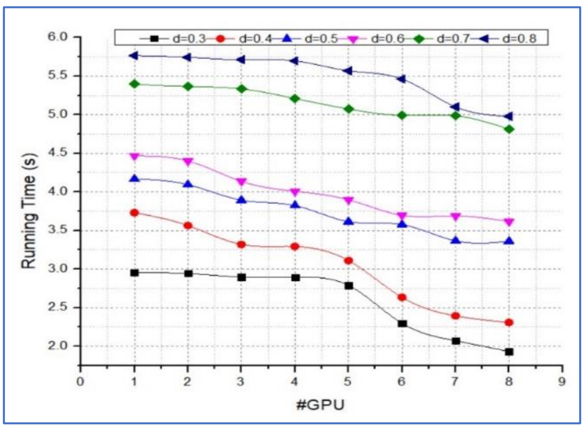
(d) Dataset 4

Fig. 3: Speed-up analysis for different datasets using the GPU

The fuzzy integrated rough set theory successfully analyzed the data involved in the smart city very quickly. The GPU processed the request according to the neighborhood values. The relation matrix was computed for all dataset information that effectively predicted the resources. Likewise, the approach required a minimum running time to process the user request, and the system's efficiency was evaluated using various dataset information. A graphical analysis of the running times is illustrated in Figure 4.



(a) Dataset 1



(b) Dataset 2

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

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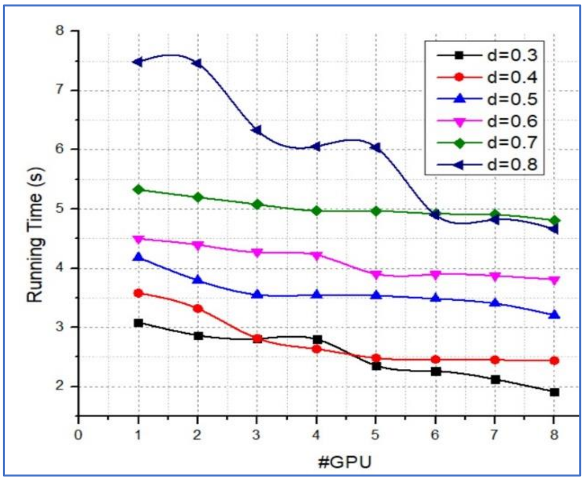

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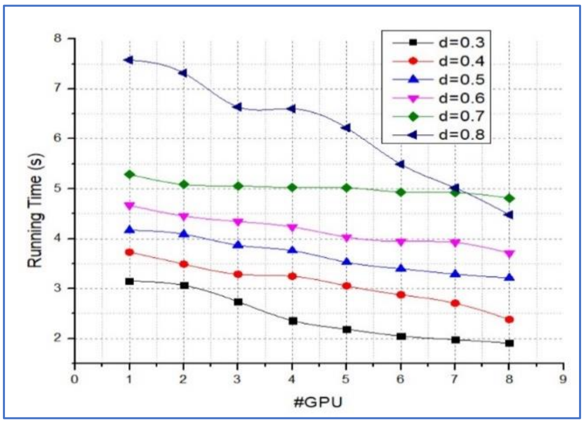


(d) Dataset 4

Figure 4: Running time analysis for different datasets using GPU

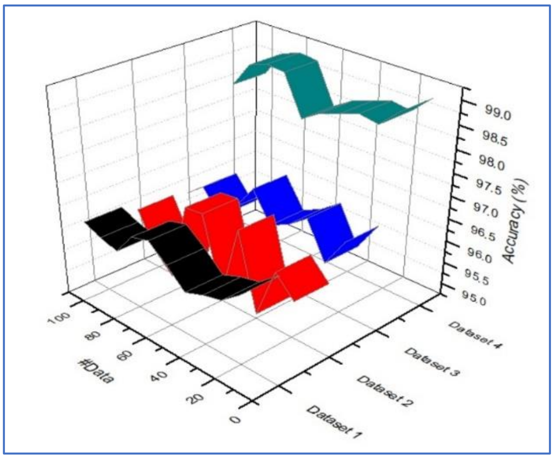
Here, the vehicle traffic data, pollution dataset, weather dataset, and parking dataset information were utilized to explore smart city construction. The neighborhood relation matrix was computed for every dataset to satisfy the user requirements. The computed neighborhood relation, Figure 5(d), ranged from 0.3 to 0.8 because the user request had a minimum neighborhood value; therefore, the GPU processed the information with a minimum running time.

The high neighborhood value indicated that the GPU consumed the maximum running time. The minimum and maximum running times indicate that the fuzzy incorporated rough set approach recognized the boundaries of the data and processed the user request effectively. The above discussion shows how the introduced approach processes user requests with a minimum running time and increased the speed for different relations. In addition, IoT data classification should have been performed with high forecasting accuracy. The accuracy obtained for the different datasets is illustrated in Figure 5.

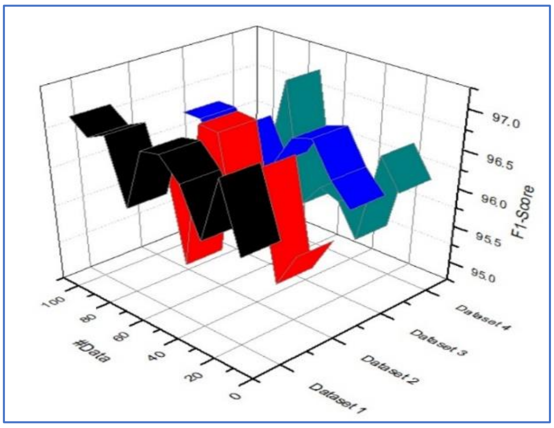
Here, the network utilized multiple layers that processed the inputs according to the weights and other network parameters. The tanh activation function and gradient descent function were utilized to compute and predict the output value for every input. The rough set algorithm used the upper and lower approximation regions to identify the smart city data analysis changes. The algorithm used the AdaBoost learning process, which trained the features with the help of a label value, leading to minimizing the classification error rate. The minimum error value caused high prediction accuracy. Therefore, the smart city changes were easily adapted and effective in the DT and BIM structures.

DOI: 10.17148/IJARCCE.2023.12301

The algorithm used neighborhood relation selection, and each decision was carried out according to the learning function that helped to resolve the misclassification error rate. Further, the excellence of the introduced FRST with MNM approach was compared with existing methods, such as the DT-based deep learning approach (DT-DLA) [20], fuzzy rules with Bayes network (FR-BN) [21], DT with fuzzy logic (DT-FL) [22], and edge intelligent federation learning (EIFL) [24]. The obtained results are illustrated in Tables II (a)–II(d) with the different dataset information.



(a) Accuracy



(b) F1-Score

Fig.7: Efficiency Analysis

TABLE II (A): EFFICIENCY ANALYSIS - DATASET 1

Metrics	DT-DLA	FR-BN	DT-FL	EIFL	FRST with MNM
Accuracy	94.78	95.39	95.89	96.28	97.86
F1-Score	94.18	95.72	96.28	97.398	98.39
Mean Square Error Rate	0.675	0.5754	0.476	0.386	0.196

Findings: Table II (a) clearly shows that introducing FRST with MNM-based developed BIM smart city construction improved the accuracy by 2.097%, the F1-score by 2.67%, and minimized the error rate up to 62.03% when compared to the other methods.

International Journal of Advanced Research in Computer and Communication Engineering
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TABLE II (b): EFFICIENCY ANALYSIS - DATASET 2

Metrics	DT-DLA	FR-BN	DT-FL	EIFL	FRST with MNM
Accuracy	96.38	97.33	97.98	98.23	98.48
F1-Score	95.78	96.86	97.39	98.145	98.78
Mean Square Error Rate	0.657	0.475	0.353	0.286	0.096

Findings: Table II (b) clearly shows that introducing FRST with MNM-based developed BIM smart city construction improved the accuracy by 1.02%, the F1-score by 1.79%, and minimized the error rate up to 78.18%, when compared to the other methods.

TABLE II (C): EFFICIENCY ANALYSIS - DATASET 3

Metrics	DT-DLA	FR-BN	DT-FL	EIFL	FRST with MNM
Accuracy	95.79	96.97	97.39	97.84	98.37
F1-Score	96.19	96.83	97.27	97.93	98.02
Mean Square Error Rate	0.457	0.367	0.307	0.265	0.103

Findings: Table II (c) clearly shows that introducing FRST with MNM-based developed BIM smart city construction improved the accuracy by 1.42%, the F1-score by 0.99%, and minimized the error rate up to 70.48%, when compared to the other methods.

TABLE II (D): EFFICIENCY ANALYSIS - DATASET 4

Metrics	DT-DLA	FR-BN	DT-FL	EIFL	FRST with MNM
Accuracy	96.28	96.87	97.28	97.86	98.37
F1-Score	96.86	97.38	97.80	98.38	98.97
Mean Square Error Rate	0.54	0.462	0.375	0.286	0.11

Findings: Table II(b) clearly shows that introducing FRST with MNM-based developed BIM smart city construction improved the accuracy by 1.0%, the F1-score by 1.40%, and minimized the error rate up to 73.49%, when compared to the other methods. Thus, the FRST with MNM framework successfully identified smart city changes with a minimum error rate. The minimum deviation error directly shows that the introduced approach effectively resolved high-dimensionality and classification issues. In addition, for every change, the DT technology created a copy for the smart city that reduced data destruction and improved overall performance.

V. CONCLUSION

This paper analyzed a smart city construction process based on GPU integrated fuzzy rough set theory (FRST) and a multi-perceptron neural model (MNM). Initially, the smart city-related requirements, plan, operations and management, and renovation procedures were collected. The gathered information was processed with the help of the BIM framework to construct the smart city in an effective manner. The developed smart city made a copy with the help of DT technologies

ISO 3297:2007 Certified ⁕ Impact Factor 7.918 ⁕ Vol. 12, Issue 3, March 2023

DOI: 10.17148/IJARCCE.2023.12301

that reduced data destruction and improved overall smart city performance. During this process, the GPU analyzed the amount of data with a minimum running time and a maximum computation speed.

A user request in the smart city was further evaluated using a classification approach. The MNM approach recognized changes in the dataset, which helped forecast smart city performance. The classifier utilized the AdaBoost learning algorithm to reduce weak classifications and the classification error rate. The discussed system used the CityPulse dataset, which consists of several types of information about a smart city. The introduced approach successfully recognized changes for the entire dataset and improved the overall smart city performance. An optimization algorithm will be incorporated with the classification model to maximize system performance.

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