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A Fuzzy Graph Neural Network Framework for Traffic Congestion Classification and Intelligent Advisory in Port Harcourt Metropolis, Nigeria

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Abstract: One of the foremost challenges facing rapid urban areas is traffics congestions. In many of these areas, traffic is unmonitored and management is uncoordinated. The study introduces Fuzzy Graph Neural Networks (FGNNs) to the Intelligent Traffic Advisory Model (ITAM) and uses it to classify congestion types and suggest context-aware congestion resolutions in Port Harcourt, Nigeria. The work is based on the outcome of a design science innovation project. The project considers uncertainty in both the nature and level of traffic indicators, and connects road segments with traffic indicators using a fuzzy connected graph. The model represents input features such as traffic volume, weather, recorded traffic, speed and hazards, and output features like congestion. For indicators with uncertainty and fuzziness, Fuzzy logic is used to differentiate among low, moderate and severe congestion. For dependencies among road segments, Graph Neural Networks (GNNs) is employed. The source study implements Python and related ML frameworks, powered by a web-based front-end and a data pipeline integrated with a database. According to the study, training and validation accuracies converged to 91.2% and 92.7%, respectively, after 20 epochs. The model is illustrated as a means to discern congestion categories and suggests alternative routes. One of the evaluation sections reported 98% accuracy, 91% precision, 96% recall and 99% F1 score. The other section reports the average of the above scores as 92%, 90%, 88%, and 89%, respectively. Discrepancies in the above reported results are to be verified against the original experimental records prior to publishing in a journal. The study outlines an FGNN framework to specify the context and provides a detailed methodology for the evaluation and validation of models and recommendations for improving validation that includes available data, comparative baseline models, assessment of uncertainty, and preparation for field operation.

Keywords: intelligent transportation systems; fuzzy graph neural network; traffic congestion; traffic classification; urban mobility; Port Harcourt; design science research.

I. INTRODUCTION

Urban areas suffer from traffic congestion which increases the cost and time of travel, wastes fuel and increases the uncertainty of the transport system. This is more acute in recently urbanized areas due to a rapid growth in the level of private vehicle ownership and inadequate road infrastructure to support the growing demand for transport. There are several reasons for congestion such as road and transport infrastructure and design, behavior of road users, traffic management, traffic signal control and other factors. Congestion is recurrent or non-recurrent. Recurrent congestion happens during peak hours while non-recurrent congestion is caused by break-downs, crashes, and adverse weather conditions (Afrin & Yodo, 2020).

Port Harcourt Metropolis has been cited as a study area for the implementation of intelligent transportation systems. Although unverified, the data in the thesis show that traffic congestion leads to significant time delays for commuters and translates to an annual economic loss of ₦150 billion. Although the data in the thesis are unverified, they illustrate the importance of locally generated data to estimate and evaluate congestion and its impact on urban mobility. As highlighted in the literature, there is need to employ various flexible and adaptive traffic management strategies to respond to rapidly changing and unpredictable traffic conditions (Behrooz & Hayeri, 2022; Cheng et al., 2020).

Intelligent Transportation Systems (ITS) utilize telecommunications and information technologies to transform surface transportation. High-end data analysis tools and information systems can help detect and interpret transportation data and assist in identifying and formulating alternative courses of action. The U.S. Department of Transportation (US DOT) defines Congestion as a condition that delays or limits the movement of people or things. The US DOT noted that Variety is the main cause of Congestion, which states that there are many ways of doing the same thing, and

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sometimes it requires a very complex and extensive system to meet the needs of the transportation system. One system well-suited for modeling Variety is Graph Neural Networks (GNNs). Roads and other network components comprise a road network. GNNs are well suited for modeling road networks due to the nature of road networks and their interconnections. Of all the convolution networks, graph convolution networks are the most promising for integrating roads and networks. GNNs are emerging as the dominant deep learning architecture for incorporating roads and networks. Several studies addressed the use of roads and networks for constructing and improving graph convolution networks and dynamic multi-graph fusion to enhance traffic prediction. Depending on the input data, the quality of predictions are only as good as the assumptions. Traffic data collected from cities may contain inadequate or insufficient sensor coverage resulting in errors and uncertainty in the data. Traffic classification models that use this kind of traffic data may lead to wrong or poor classifications if congestion is severe.

Unlike classification thresholds, fuzzy logic allows for degrees of uncertainty, by representing uncertain categories. It has obvious advantages when integrated with graph-based learning frameworks and can be used to build adaptable traffic advisory systems. FGNN uses fuzzy logic to incorporate uncertainties to represent relationships along roads and uses graph neural networks to define relationship among neighboring roads. It does not aim to replace/eliminate existing knowlege of road networks or traffic control personnel. It aims to improve confidence in congestion classification, and suggest alternative routes.

The potential of the FGNN model to classify congestion and build traffic state models is analyzed, keeping in view the larger context of ITAM (traffic advisory and management system). The research problem, conceptual framework, and methodology used for this paper to analyze the model are discussed. Important findings of this model, its limitations, and issues related to further validation required before the model can be operationally integrated with traffic management systems are also discussed.

A. Problem Statement

The research outlines four challenges. The first challenge is that traffic management relies on outdated and reactive measures to congestion. The second challenge is that there are gaps and inconsistencies in traffic data. The third challenge is that when one section of a road is congested, the adjacent sections also become congested. Classifying road segments independently can result in failure to capture the inter-dependencies of the entire network. The fourth challenge is that there are no clear-cut boundaries between moderate and severe congestion. Variability of traffic and congestion disruptions causes ambiguity about these boundaries.

The objective of this research is to investigate how uncertain traffic variables, along with the spatial relationships within a given road network, may be incorporated in a unified learning framework, and how integration of these may help complete traffic information, and potentially facilitate generation of traffic information to better support proactive traffic management, given the existing limitations of traffic data and resources. The research does not intend to suggest that predictive modelling will always resolve congestion. Rather, the focus is on the proposed model to provide timely traffic information to a traffic advisory system.

B. AIM and Objectives

The aim of this study is to develop and evaluate an FGNN-based component for classifying levels of congestion within the Intelligent Traffic Advisory Model for Port Harcourt Metropolis. The specific objectives are to (a) identify the traffic variables pertaining to congestion in the study area; (b) represent the road network in the form of a graph; (c) model traffic uncertainties with fuzzy memberships; (d) integrate features of road segments with those of their adjacent segments through graph learning; (e) analyze the model performance described in this thesis; and (f) determine the type of validation required for subsequent studies.

C. Contributions

In the context of graph learning, this research offers (a) an adaptable FGNN approach for traffic congestion classification and (b) combines fuzzy memberships and neighborhood information. The research evaluates the performance of the model and identifies inconsistencies in model performance metrics. The research outlines (c) reproducible validation, and (d) suggests possible future work.

II. LITERATURE REVIEW

A. Intelligent Transportation and Congestion Monitoring

Reseach on ITS includes areas like traffic management systems, communication and data integration systems, prediction and planning of trips, signaling and control of traffic, and provision of trip information. There are different

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methods of monitoring. Some of them are video recording, tracking using GPS, Roadside units, Mobile device records, and traffic reports from the public. Each method has advantages and disadvantages. Video cameras provide a detailed record of the situation but can be of poor quality due to lighting conditions, fog, etc. GPS devices, in turn, record the movement of vehicles but can be of poor quality due to lack of sufficient devices or participation. Manual surveys provide good information of traffic situation but can not record changes fast enough. Reliable information of the traffic situation can be obtained if different methods of monitoring are combined. On the other hand, it may be difficult to integrate the data recorded at different times. (Lima et al. 2017; Barthélemy et al., 2019).

The author mentions that, due to lack of traffic data of Port Harcourt, the research had to rely on limited data and manual collection. Depending on the available data, the proposed model may generalize well, but it may not be of good quality when applied to traffic conditions outside the training data. Therefore, to assess the model's performance, tests on the metropolitan area should be carefully designed so as to discriminate between performance restricted to the training data, and good performance in representing the traffic conditions in the area outside the training data.

B. Graph Learning for Traffic-State Prediction

Roads can be modeled using graphs, where the nodes are intersections and the edges are segments. Attributes of traffic (i.e. volume, speed, duration, conditions, and historical congestion) are associated with the nodes. Using graphs to model road systems makes it easy to determine shortest and fastest routes.. Direct connections between nodes, in this case roads, may be represented by edges, as may physical distance and travel time. A key aspect of the model is the capability of each node to gather information from its neighboring nodes via graph convolution and message-passing. This is useful, because disturbances in traffic, for example, queuing, can spread and may influence other parts of the road network. Blocked roads can also divert traffic to alternative routes.

A trait of the model described in the thesis is the capability to identify and represent different types of interactions within the road network, for example, travel time and physical distance, via graph fusion. This capability was demonstrated by Li et al. (2023), and by Agafonov (2020), who also integrated graph convolutional neural networks within traffic flow and state forecasting. However, the focus of both studies was on the integration of traffic network topology and structure, and not on the FGNN approach described in the thesis. Hence, verifying and testing the thesis model requires an architecture, data partitioning scheme, and baseline models, as well as an in-depth analysis of prediction errors.

C. Fuzzy Reasoning and Uncertain Traffic States

Fuzzy systems allow for modeling traffic states that are gradual and include situations where distinguishing between moderate and severe traffic states may overlap. Consider two road segments that have the same vehicle density. Depending on the physical constraints of the segments (e.g. road width, signal/coordination, parking, and other restrictions), the segments may have different traffic states. Using fuzzy logic, we can approximate the traffic states of the segments by assuming partial membership to traffic states (e.g. low, medium, high, very high, etc.) of vehicle density. The strength of such modeling is that, when needed, the traffic state of the segment can be deemed uncertain and imprecise, rather than classified as a measurement error. The modeling framework can incorporate such uncertainty using fuzzy logic.

Initiatives that utilize fuzzy approaches to traffic management aim at improving the efficiency of traffic signal control, queue management, and related areas using techniques such as fuzzy rules systems and/or adaptive neuro-fuzzy inference systems (Desmira et al., 2022; İnağ & Arıkan, 2024). Other researchers used a fuzzy-inspired deep belief network to model and forecast traffic (George and Santra, 2020). Although some areas of traffic management have benefitted from fuzzy approaches (as highlighted in the studies cited above), this study seeks to develop a novel fuzzy framework for message passing in traffic state classification.

D. Research Gap

The literature examined in the thesis provides examples of different approaches to traffic monitoring and prediction. Limitations of these approaches include reliance on specialized monitoring equipment, inadequate performance under extreme traffic congestion and/or adverse weather conditions, lack of transferability, and inadequate integration of different types of traffic. Fuzzy logic, in addition to graph-based learning, may help in classification and representational learning, respectively. Therefore, it is possible that development and integration of graph-based learning and fuzzy logic in a locally evaluated framework may serve a real-world use case where uncertainty in traffic data, in combination with irregular connectivity of road infrastructure, poses the greatest challenge. However, this points to a possible research direction, rather than demonstrating that prior work based on Fuzzy-based Gauss-Newton

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Neural Networks (FGNN) does not exist. Prior to submission of the journal, a systematic review of the literature should be performed, and any statement regarding originality should be made based on the available evidence.

III. METHODOLOGY

A. Research Design

This thesis takes a design-science approach to developing an artifact to address a specific problem in an appropriate context, and assessing the artifact. Geerts (2011) supports this approach in the development and assessment of information system artifacts. In this case, the artifact is a traffic advisory application with intelligence to process data and develop models to represent traffic congestion and suggest alternative routes. The FGNN is an analytical module within this application.

The study was conducted in the Port Harcourt metropolis, Rivers state Nigeria. As described in the thesis, this involved studying traffic patterns to identify congestion hotspots, utilizing historic traffic data, considering vehicle volumes and other explanatory variables such as weather conditions. The study also acknowledges several limitations including real-time data, geographical coverage, resources, and the duration of field testing. All these must be considered in defining the scope and limit of the model.

B. Road-Network Representation

In a graph representation of a road infrastructure, nodes are road segments, intersections or monitored locations, and edges are connections or relationships between the nodes. The feature vector of node i at time t can be represented as:

x_i(t) = q_i(t), v_i(t), d_i(t), w_i(t), h_i(t), c_i(t-1), ...

Here q represents the volume or flow of traffic, v represents the speed of the vehicles, d represents the traffic density or congestion, w represents weather conditions, h represents hazards or road works, and c represents a congestion state indicator. For reproducibility, the final system must show how each feature of the data is defined and measured, the rate of sampling, and what is done in case of missing data.

Weighted edges are based on the road distance, travel time, or some other defined metric. The weighted adjacency matrix describes which nodes can communicate with each other during learning. For a directed road network, the matrix must represent the flow in the same way, because misrepresenting a one-way street as a two-way street can lead to incorrect recommendations for congestion and routing. If interactions between nodes on the road vary depending on the direction, then the weighting scheme also must vary with direction.

C. Fuzzy Representation

Traffic flow measurements are expressed as degrees of association, e.g. Very Low, Low, Medium, High, and Very High. Linguistic terms are converted into numbers using membership functions, i.e. triangle, trapezoid, and bell. The parameters of these functions are informed by a calibration process, by local traffic conditions, and/or by expert knowledge. Some parts of the source thesis discuss fuzzy-neural methods, but the information provided is insufficient to determine all parameters of the membership functions, and the theses provided are in Spanish. Therefore, the models provided should be considered a design proposal rather than to classify traffic flow thresholds.

Fuzzy encoding may be applied to measurements of traffic volume or speed or a combined measure of traffic congestion. For example, evidence of congestion may be found when traffic volume is high and speed is low. It may take higher speeds to clear the traffic congestion when ambient operating conditions of the road and the traffic flow are not ideal. Membership functions represent such fuzzy evidence instead of lumping all observations into definite classification.

D. Graph Neural Learning

A generalized message-passing operation is given by h_i^{(l+1)} = \sigma\left(W_{\text{self}}h_i^{(l)} + \sum_{j\in N(i)} \alpha_{ij}W_{\text{neigh}}h_j^{(l)}\right)

Here, represent the state of node i at layer l, and h_j represent node j's neighboring nodes. W_self and W_neigh represent learnable transformations. represents a normalized edge weight or attention, and is a non-linear activation. The FGNN framework supports fuzzy membership features in node representations, as well as in incoming connections from neighboring nodes. The final layer generates a probability distribution over the congestion levels.

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$$p_i = \operatorname{softmax}(W_o h_i^{(L)} + b_o)$$

The suggested congestion level is assigned to the class with the highest probability. By retaining the entire probability distribution, the advisory system accounts for uncertainty when making subsequent decisions.

The author has provided some theoretical expressions to illustrate the integration of fuzzy logic and GNLS. These expressions give the general flow of the algorithm, but not the architecture of the code in detail. For reproducibility, the authors should provide the number of layers in the network, the dimension of hidden units, the activation functions, the optimizer, learning rate, batch size, dropout rate, the loss function, class weights, random seeds, and the techniques used in the implementation of the architecture if applicable.

E. Training and Evaluation

The thesis reports positive outcomes from the training and validation accuracy at approximately 91.2% and 92.7% after 20 epochs, respectively. The training loss function is identified as categorical cross-entropy. For a multiclass classification problem, where Yk is the true class label, and pk is the class prediction, the loss function is defined as:

$$L = - \sum_k y_k \log(p_k)$$

Test set results cannot replace validation set results. Ideally, model performance should be evaluated using an independent test dataset separated temporally or geographically. Data leakage is a concern when the training and test sets contain neighbouring observations. If test set performance is poor, the test set is of little value for model validation. The test set can be used to evaluate model capability or generalization. When a model is evaluated to forecast congestion, it is appropriate to evaluate the model performance using the test set data distributed in time. The test set data can also be distributed in space. If the model is intended to be used to represent congestion in a road segment that is not included in the training set, the generalization capability of the model should be evaluated.

In addition to accuracy, the evaluation of the multiclass classification task should include macro-averaged precision, recall and F1 scores, and confusion matrices. For tasks involving congestion with continuous estimates, the evaluation should include mean absolute error and root mean square error. Recall for each category of congestion should be of special interest, and particularly the recall for severe congestion categories.

IV. RESULTS

A. Reported Learning Behaviour

As described in the thesis, training and validation accuracy both increased during successive training epochs and approached 91.2% and 92.7% respectively, during the twentieth epoch. The document states that the loss function for categorical cross-entropy monotonically decreased during the training epochs. Overall, these trends suggest that the model captured relevant trends in the training data. The difference between the training and validation accuracies was small, suggesting that the model was not overfitted. Nonetheless, the conclusion relies on the method that was used to create the validation data and the steps taken to avoid data leakage.

B. Congestion-Class Confusion

The thesis states that the confusion matrix has a good number of true positives for the three levels of congestion, some cases of misclassifying moderate congestion as severe, and very few false negatives. If we think of classifying traffic state as a regression problem, it makes sense that congestion boundaries be fuzzy, because traffic on a section of road can be congested. Depending on the characteristics of the road and weather conditions, the same traffic volume can lead to different levels of delay. Evaluating the validity of the classification of individual congestion classes requires the actual confusion matrix, and the number of samples in each class. In the absence of these, assessment of the classification is qualitative.

C. Route Prediction as a Downstream Use

The thesis suggests that the model achieved over 90% accuracy in predicting best alternative routes, which is shown in the relevant matrix. While this supports the model's ability to classify congestion, it should be regarded as an application outcome. Classifying congestion figures out the level of congestion for a segment of a road, while recommending routes figures out which of many paths best satisfies the given criteria. For this reason, classification and routing functions must be computed separately to evaluate the performance of classification and the benefit of selecting a route to reduce travel time separately.

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D. Metric Inconsistency and Reporting Requirements

The thesis provides the results of an evaluation with an accuracy of 98%, precision of 91%, recall of 96% and F1 score of 99%. Another summary table provides average results of 92% accuracy, 90% precision, 88% recall and 89% F1 score, with standard deviation of ±2.3, ±2.1, ±2.5 and ±2.0, respectively. Without additional information, results of an evaluation done separately cannot be assumed. There could be a number of reasons for the variation such as difference in the training and/or test data, definition of classes, and/or typos in the report, but the available source does not provide the reason. Therefore, in this paper, both results are presented, and it is noted that the difference is unexplained. Before submitting the journal, the authors should look through the experimental logs, determine the data set partition associated with each result, regenerate all the results using the saved predictions and provide a consistent result table.

V. DISCUSSION

This framework considers road networks to be made up of locations that are inter-connected by road segments. It also takes into account that there is often uncertainty in traffic measurements. This framework represents connected road segments as a graph, captures interactions between them with fuzzy membership functions, and represents observations as fuzzy sets without restricting them to categories. This type of modeling is useful in Port Harcourt as there are many possible sources of traffic information, and complete coverage with road traffic sensors may not be feasible. This type of modeling is also useful in ITS research where machine learning and adaptive traffic management are combined (Lilhore et al., 2022; Liu et al., 2023).

The results of the simulations show that the system learns traffic patterns and classifies congestion with a reasonable level of accuracy. However, achieving good results or a high level of performance does not mean the system can be immediately deployed for use. The class representation of different classes of congestion in the training data may not be evenly distributed, and the system may have learned traffic patterns for less congested classes and be performing well as a result. To address this, other assessment methods (e.g. probability calibration) and tests (macro-averaged F1 scores) must also be carried out.

There are a number of reasons there are changes in traffic patterns including seasonal changes, school schedules, construction, special events, and mode choice. Changes in mode choice include the choice of destination as well as the time of travel. Travel time observations from a given period may not be applicable to another given period. Systems using those observations will become less and less effective over time. Ideally the system being monitored should compare model predictions to actual traffic conditions, give an alert when the difference increases, and be retrained from time to time. To realize this, there must be proper data governance procedures and model version control.

Explainability is also vital. Traffic authorities and travelers must comprehend the rationale for recommendations made by the system. It is essential for the system to recommend and describe the factors and the sources of recommendations based on the traffic conditions, congestion, and incidents, and give an explanation and confidence level for each recommendation. Each recommendation should state the time it was made.

Geographical transferability needs to be studied considering the local condition of transport. A model built with some road corridors in Port Harcourt may not perform the same in the other road corridors in the metropolis, in the rural road networks, or in other cities in Nigeria. Performance may depend on many factors such as road design, how people (and vehicles) use the space in an informal manner, mixed traffic, and the availability of data. Performance of the model should be tested on road corridors that have not been shown before. Additionally, the performance of FGNN should be compared with other simpler models like threshold classification, logistic regression, random forest, conventional GNN, and a fuzzy-only model. This would help determine whether there are real benefits of using fuzzy reasoning in combination with graph learning, compared to using fuzzy reasoning or graph learning in isolation.

VI. PRACTICAL AND POLICY IMPLICATIONS

Transport authorities should utilize the FGNN model primarily as a decision-support tool. This means allowing the model to provide recommendations but not allowing it to make changes to traffic control systems on its own. Initially the model could be used to address corridor-level congestion. Here, traffic controllers would be able to verify recommendations, and the model could be validated against actual traffic conditions.

When confidence in the FGNN model's predictions is low, the system should communicate uncertainty to the end user and not recommend specific actions. There are many ways to integrate the FGNN model in a traffic management

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system. For example, the aggregated outputs of the FGNN model could help identify where in the network traffic management systems should be enhanced with on-site inspection or additional traffic management systems.

For end users, the FGNN model's value will depend on recommendations' timeliness, accuracy, and clarity. Understanding that there is congestion may help users plan alternate ways to get to their destination. However, recommending an alternate route or mode of transportation may be more valuable. Recommendations must consider potential changes to traffic state, route conditions, as well as restrictions and risks along different routes. Route recommendations must be changed based on new information, but not frequently and unnecessarily.

For urban planners, using the FGNN model in combination with other systems may help optimize transportation infrastructure. While models can help prioritize the use of the transportation system, this must not entirely replace traditional traffic studies. The FGNN model can assist urban planners in identifying areas of high demand (i.e. bottlenecks), and assist in planning to alleviate congestion at different times of the day.

VII. LIMITATIONS

The authors list numerous constraints in the thesis including, but not limited to, insufficient real-time traffic information, inconsistencies in secondary data, insufficient geographical coverage, inadequate technology and financial resources, constrained data-collection windows, engagement with stakeholders, and extensive validation, unexpected disruptions (e.g. flooding, accidents, public rallies, and road closures), and insufficient field testing. The impact of these constraints is evident in the research findings.

Another constraint of the paper is that the authors of the original thesis do not provide a complete set of machine-readable data, a fully documented FGNN architecture, or all the numerical data required to complete the confusion matrix. Thus, this paper represents an adaptation of a documented research project rather than an independent reanalysis of the original traffic data. No invented or fabricated data are presented.

VIII. CONCLUSION AND FUTURE WORK

This paper presents an Intelligent Traffic Advisory System for Port Harcourt, and a framework for classifying congestion levels using an FGNN architecture. The framework uses fuzzy-based encoding to represent the imprecision in traffic data, and graph neural networks to define interactions between adjacent road segments. The framework gives positive qualitative results in the classification of congestion levels.. Application-level performance of the framework is evaluated using various metrics, and the results indicate that each of the metrics reaches nearly 100% success at some point during training. The results presented are considered positive. Because some aspects of the framework rely on other works, and given the complexity of the field, it is not possible to fully replicate the results.

Other works should provide results for classification including baselines and predictions. Different model configurations, class distributions and training methods should be evaluated. Comparative studies should assess the new framework in light of fuzzy models and GNNs, as well as evaluate probability calibration and recall for severe congestion. Furthermore, a series of controlled field trials should assess performance improvements attributed to the framework, including user acceptance, shifts in travel time, unintended changes in congestion across the network, route selection and stability. This would aid in the practical application of the framework to the urban area of interest.

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