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A Conceptual CNN–LSTM Framework for Acoustic Traffic Congestion Forecasting on Low-Cost Edge Computing Platforms

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ABSTRACT

Traffic congestion in urban areas is still one of the key obstacles of intelligent transportation systems at present, which has implications for mobility, energy consumption, and environmental sustainability. Current methods in traffic monitoring have been based on infrastructure-intensive sensing technologies such as cameras, inductive loop detectors, and GPS-based methods, which are generally expensive and sensitive to environmental conditions. In the meantime, acoustic traffic monitoring has recently proved to be a cost-effective and robust method by making use of traffic-generated sound patterns to infer traffic conditions. Some previous research showed that deep learning models, especially Long Short-Term Memory (LSTM) networks, could produce high classification accuracy in acoustic traffic analysis with real-world datasets. But most existing approaches are only directed towards recognition of traffic states without considering the need to predict traffic congestion forecasting. In this paper, we implement a conceptual hybrid CNN–LSTM for acoustic traffic congestion forecasting on low-cost edge computing platforms for analysis. Furthermore, the framework extends previous classification-based work by rendering the question as a time-series forecasting problem. Both Convolutional Neural Networks (CNNs) are used to extract spectral representations from acoustic feature maps together with LSTM networks to capture temporal dependencies in sequential traffic patterns. This unified architecture promotes prediction-based traffic analytics while offering compatibility for resource-constrained edge devices. The proposed framework is constructed on top of pre-validated acoustic traffic datasets and experimental findings, thus lays the methodological basis for further forecasting-centered applications. It is accepted that the current study lacks experimental validation, and a complete examination, including comparison with baseline models using forecasting metrics, such as MAE and RMSE, is suggested as future work. In summary, the presented CNN–LSTM framework provides a structured basis to advance acoustic traffic monitoring beyond classification to forecasting-based intelligent transportation applications.

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1. INTRODUCTION

Traffic congestion remains a major challenge in modern intelligent systems, especially in densely populated cities that have rapidly increasing vehicle demand. Travel time reliability, fuel consumption, air quality, and overall transportation efficiency are negatively affected by rising traffic volume. Because of this, traffic monitoring and congestion analysis have attracted considerable attention as active areas of research in intelligent transportation systems (ITS) and smart city applications [1], [12], [13]. Traditional traffic monitoring systems usually include infrastructure-heavy sensors, which can be surveillance cameras, inductive loop detectors, radar sensors, and GPS-based vehicle monitoring systems. While they can yield important traffic insight, they commonly carry significant installation and maintenance costs. Furthermore, some such systems, especially vision-based systems, are also susceptible to environment-induced problems such as poor lighting, weather disturbances, occlusion, and others, causing them to lack reliability in urban system-level settings as some of the models are based on vision. Acoustic sensing has emerged in recent years as an alternative low-cost traffic monitoring method. Traffic-related sound from vehicle engines, tire-road interactions, and other traffic activity contain useful information that can inform traffic conditions. Acoustic sensing does have several practical advantages over camera-based methods such as low cost, straightforward implementation, and reduced sensitivity to illumination conditions. The characteristics of its structure make it especially adaptable in edge-based and low-resource intelligent traffic systems [1], [3], [4]. Acoustic traffic analysis can be realized with the help of machine learning and deep learning models, which have been shown in the literature previously. Classical techniques like Support Vector Machines (SVM), Random Forests (RF), and Artificial Neural Networks (ANN) have been used to analyze handcrafted acoustic features such as Mel-Frequency Cepstral Coefficients (MFCCs), spectral centroid, spectral bandwidth, and zero-crossing rate [1]–[4]. To improve their ability to learn complex acoustic patterns, deep learning techniques have shown improved capability. Specifically, Long Short-Term Memory (LSTM) networks showed excellent performance in modeling temporal dependencies of traffic-related acoustic signals [5]–[11], and a previously reported real-time acoustic traffic monitoring study confirmed the benefits of LSTM architectures for traffic congestion classification using both real-world and common benchmark datasets [16]. While presented this way, these findings set a strong baseline for recognizing acoustic traffic states, most current efforts attempt to do so using classification-related tasks, where the focus is on identifying the current state of traffic instead of forecasting future congestion behavior. On the topic of intelligent transportation, prognosticating future traffic congestion is often better than merely identifying the present traffic condition. Short-term traffic forecasting has a huge bearing on more proactive traffic management techniques like adaptive signal timing, routing, and congestion management. Driven by this need, the present study introduces an extension of the concept of acoustic traffic monitoring from being a reactive classification tool to a predictive one, forecasting traffic congestion in the near future. We achieve this by proposing a hybrid CNN–LSTM framework for the model of spectral and temporal characteristics of traffic-related acoustic signals along with compatibility of the framework together with low-cost edge computing platforms. Unlike the majority of existing works (e.g., LSTM with the network), which focus on traffic state classification, this work specifically addresses the methodological transition to forecasting using acoustic data at the edge.

1.2 Research Gap

As much as they have attracted increasing attention towards the study of acoustic traffic monitoring, many drawbacks still exist in the literature. First, the majority of the previous-generated models consider acoustic traffic analysis in classification language and seek to classify traffic condition to detect the current one from short-term acoustic observations [1], [3], [4]. While helpful for traffic state recognition, it doesn't directly contribute to predictive congestion management. Second, a large number of all the current deep learning methods are single-stage based. CNNs are effective for capturing local spectra based on structured audio features, and LSTM models are suited for the modelling of temporal correlations among sequential signals [5]–[11]. However, little work has been done to combine the two features into a unified acoustic traffic prediction framework. Third, existing studies predominantly focused on detection and classification performance, with relatively limited attention focused on methodological formulations for short-term forecasting of congestion using sequential acoustic observations. This signifies the disconnection between existing acoustic monitoring systems and the fundamental need for action-oriented intelligent transportation applications. Last but not least, while previous studies have examined inexpensive data acquisition platforms, future-proof forecasting-like architectures are still required to be conceptually well-structured into edge-based platforms with reduced computational power. Thus, our research gaps, based on these findings, are the absence of a methodological framework to move the work of acoustic traffic monitoring beyond current-state classification and to the future-state congestion forecasts by integrating spectral feature learning and time series modeling in an edge environment.

1.3 Objective and Contribution of This Work

The objective of this study is to propose a conceptual hybrid CNN–LSTM framework for acoustic traffic congestion forecasting using low-cost edge computing platforms. The framework is intended to extend acoustic traffic classification methodologies toward a predictive formulation capable of estimating future congestion states from sequential acoustic observations. More specifically, this study aims to provide a structured methodological design in which convolutional neural networks are used to learn spectral representations from acoustic feature maps, while LSTM networks capture temporal dependencies across observation windows. The proposed framework is developed as a forecasting-oriented extension grounded in previously validated acoustic traffic monitoring approaches, thereby establishing a methodological basis for future experimental implementation and validation. This study is not intended to replicate previous work, but rather to extend it toward a forecasting-oriented formulation.

1.4 Contribution of This Study

The major contributions of this study can be summarized as follows:

1. This work moves acoustic traffic monitoring from a traffic state classification perspective to a traffic congestion forecasting perspective, moving beyond reactive recognition to proactive prediction.
2. A proposed hybrid CNN–LSTM architecture is proposed to capture both the spectral and temporal features of traffic-related acoustic signals
3. The proposed framework is developed upon previously validated acoustic traffic datasets and baseline deep learning findings provided by previous work to maintain methodological relevance to practical acoustic traffic analysis.
4. The study proposes an edge-oriented forecasting framework suitable for low-cost embedded traffic monitoring platforms at the conceptual design stage.
5. The research lays the basis for future experimental work in acoustic traffic congestion forecasting, including forecasting-horizon comparison and prediction performance evaluation based on time-series metrics.

2. Related Work

Recently, acoustic-based traffic monitoring has attracted significant interest as a more economical alternative to traditional approaches for traffic detection. Existing traffic sensing methods are generally based on infrastructure-heavy solutions like surveillance cameras, inductive-loop detectors, radar sensors, and GPS-based traffic sensors. While these technologies offer useful traffic insights, their deployment costs can be expensive and can be influenced by variables like dim lighting, occlusions, and adverse weather conditions [12], [13]. In tackling these drawbacks, researchers have investigated acoustic sensing as a different modality for monitoring traffic flows. These sounds can be used to estimate vehicle engine sounds from vehicles, interactions between tire and road, and noise from the surrounding environment, which can reveal information about traffic flow characteristics. Using signal processing combined with machine learning [1], [3] and similar methods, these acoustic patterns can be employed to identify traffic conditions including free flow, moderate traffic, and congestion states. An introduction to acoustic traffic analysis in the early days used handcrafted feature extraction in combination with classical machine learning classifiers. These commonly introduced characteristics are Mel-Frequency Cepstral Coefficients (MFCC), spectral energy, spectral centroid, and zero-crossing rate. Such features have been utilized with classifiers like Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) for traffic state classification [2]–[4]. Although a number of such approaches have proven useful, their performance relies on the engineering of features and fails to generalize to complex acoustic settings. Recent developments in deep learning have prompted the use of data-driven approaches for acoustic traffic analysis. Convolutional Neural Networks (CNNs) have demonstrated great efficacy in training hierarchical spectral representations from time-frequency audio features (e.g., spectrograms) [5], [9]. Concurrently, Recurrent Neural Networks (RNNs), in particular Long Short-Term Memory (LSTM) networks, are effective to encode temporal dependencies in sequential acoustic data [7], [10]. However, the accuracy obtained for acoustic traffic monitoring, with regard to temporal patterns of traffic conditions, has been reported to be very high during LSTM-based architectures [7], [13], [16]. These results further demonstrate the significance of temporal modeling and present Long Short-Term Memory (LSTM) as a robust baseline for sequential traffic data modeling. Nevertheless, in view of this progress, the majority of previous research is concerned with traffic state classification instead of forecasting. In the current classification-based approaches, it has been assumed that the problem is to classify only the current traffic state based on the short-term acoustic observation without explicitly modeling the temporal changes of traffic status. Such a limitation makes the application of such systems less applicable in dynamic scenarios of proactive traffic management. Furthermore, numerous deep learning methods use single-stage architectures such as CNN-based spectral feature extraction or LSTM-based temporal modeling. There has been limited work on combining spectral modeling and temporal modeling in a unified framework with respect to acoustic traffic prediction. In addition, although some works focused on real-time acoustic data collection employing low-cost platforms, the development of methodological frameworks that are specifically oriented toward forecasting-oriented traffic analysis in edge-based applications remains unfilled. Table I summarizes representative acoustic-based traffic monitoring studies to clarify existing research directions. Before now, the focus of previous studies has mostly developed on classification tasks indicated on the table, which shows that the present study aimed at addressing the research gap.

Table 1. Comparative Summary of Acoustic-Based Traffic Monitoring Studies

Study	Data Type	Feature Representation	Learning Model	Analysis Task	Real-Time Capability
Study [1]	Acoustic	MFCC, Spectral Energy	SVM	Classification	Yes
Study [2]	Acoustic	Spectral Features	Random Forest	Classification	Partial
Study [3]	Acoustic	MFCC	ANN	Classification	Yes
Study [4]	Acoustic	MFCC	LSTM	Classification	Yes
Study [5]	Acoustic	Spectrogram	CNN	Classification	Yes
This Work	Acoustic	Spectral + Temporal	Hybrid CNN–LSTM	Forecasting (Conceptual)	Edge-Oriented (Conceptual)

3. Methodology

3.1 System Overview

The aim of this work is not to mimic existing work but rather to generalise it leading to a forecasting-oriented formulation. The proposed framework is a well-defined pipeline for acoustic-based traffic congestion prediction. In contrast to classical methods that center on traffic state classification, this method reconceptualizes the problem into a forecasting endeavor in response to sequential acoustic data. This system is composed of several primary steps: the acquisition of acoustic data, signal preprocessing, feature extraction, feature normalization, and hybrid CNN–LSTM modeling. These stages are organized in a unified architecture that allows the transition from raw acoustic signals to predicted traffic congestion states. The overall workflow of this framework is depicted in Fig. 1. The most important idea behind this design is to shift into sequence-based modeling in place of independent frame-based analysis. Rather than analyzing each acoustic segment individually, the framework accounts for the temporal sequence of the observations, allowing the model to learn the evolution of traffic patterns over time. This design supports predictive traffic analysis while maintaining compatibility with low-cost edge computing platforms.

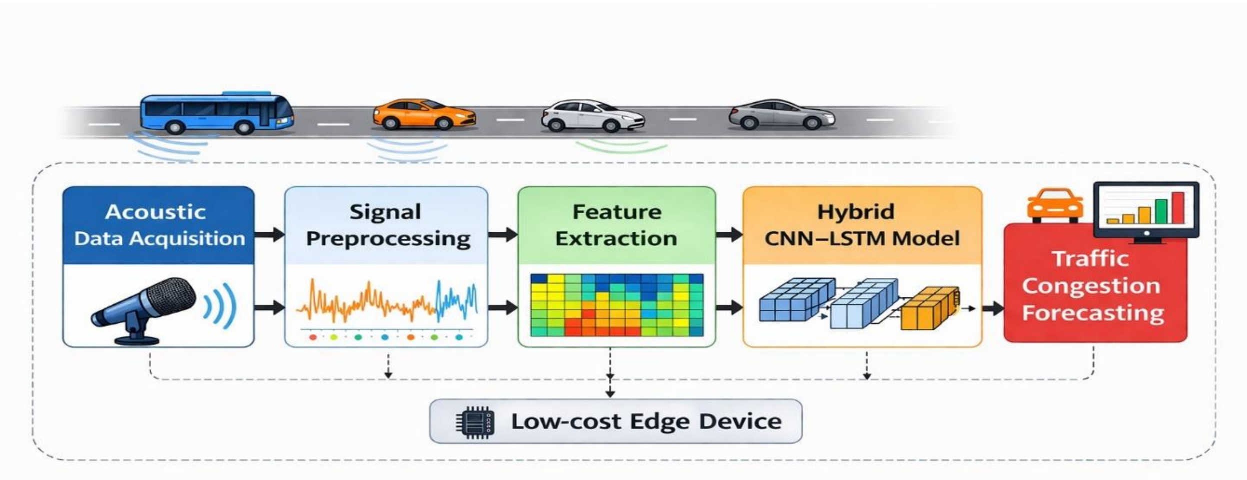

Figure 1. Block diagram of the proposed acoustic-based traffic congestion **forecasting** framework deployed on a low-cost edge computing platform

3.2 Acoustic Data Acquisition

The framework is based on an existing set of acoustic traffic monitoring methods that use low-cost edge devices for real-time collection of data [16]. These setups are often comprised of embedded processing units, directional microphones, and communication modules to listen to ambient acoustic signals. As shown in Fig. 2, the acoustic data are collected at roadside places, where vehicle-generated sounds, like engine noise and tire–road interaction, are continuously recorded. Those signals dominate and are the main informant for traffic condition analysis. Table 2 shows the acoustic data for a baseline of type used for this study: recording time, sampling rate, frame size, and features extracted. Data acquisition is approached as a validated reference in this study to match acoustic traffic monitoring scenarios in the real world.

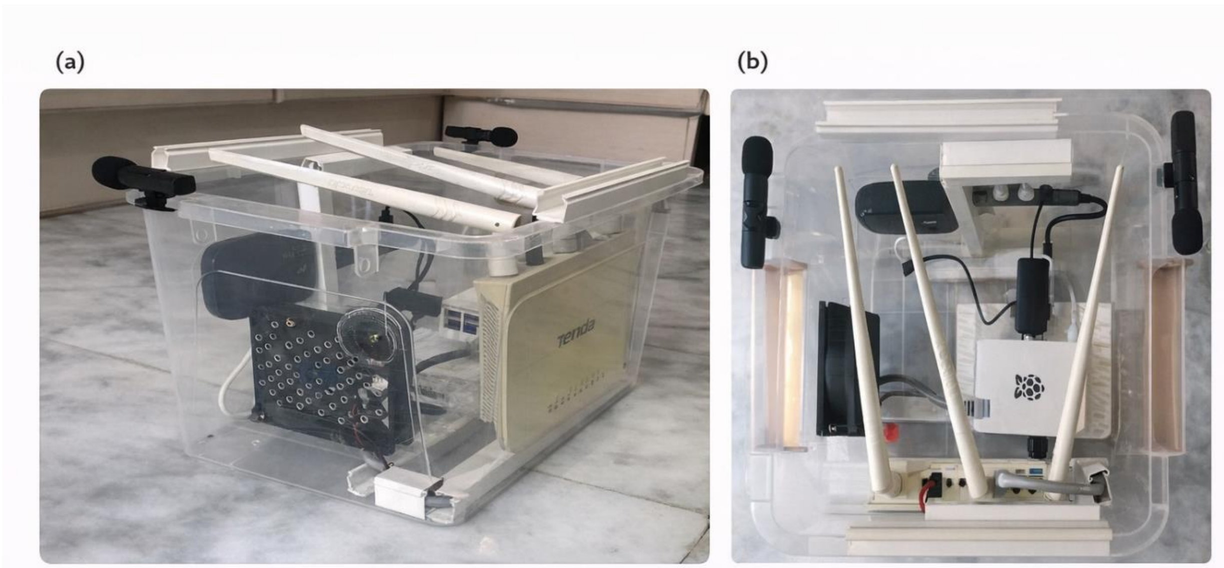

Figure 2: Acoustic traffic data acquisition platform used in the previous study: (a) external view of the hardware enclosure, and (b) internal configuration of the edge-based recording system.

Table 2. Real-Time Acoustic Traffic Dataset Summary

Parameter	**Value**
Data source	Real-time urban traffic recordings
Recording location	Urban intersection (Baghdad)
Recording duration	≈ 40 hours
Sampling rate	48 kHz
Frame sizes	40 MS, 60 MS, 80 MS, 100 MS
Extracted features	13 MFCC + spectral centroid + spectral bandwidth + ZCR
Total features	16
Traffic conditions	Normal / Moderate / Congested

3.3 Signal Preprocessing and Feature Extraction

Acoustic signals collected in urban environments can include a wide range of noise and interference sources. Thus, preprocessing is needed to convert raw audio signals into structured representations useful to model them in a machine learning context. The preprocessing step first involves segmenting the continuous audio signal into short-time frames by the sliding window method. This permits local temporal changes in acoustic profiles. Each frame is further converted to the time–frequency domain by the Short-Time Fourier Transform (STFT), which allows

The Short-Time Fourier Transform (STFT) representation of the acoustic signal is defined as follows:

$$\mathbf{X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]\, w[n-m]\, e^{-j\omega n}} \tag{1}$$

where x[n] represents the discrete acoustic signal, w[n] denotes the windowing function applied to each frame, and m represents the frame index.

Following this transformation, a collection of acoustic characteristics was obtained for traffic-related sound properties. Table 3 summarizes the feature set consisting of Mel-Frequency Cepstral Coefficients (MFCC), spectral centroid, spectral bandwidth and zero-crossing rate (ZCR). This will provide a compact and informative description with spectral and temporal features of the acoustic signal which will serve as the input to the deep learning model.

Table 3. Extracted Acoustic Feature Set

Feature Type	Description	Number of Features
MFCC	Mel-frequency cepstral coefficients	13
Spectral Centroid	Represents the spectral center of mass	1
Spectral Bandwidth	Measures the spread of the frequency spectrum	1
Zero-Crossing Rate	Number of signal sign changes per frame	1
Total Features	Combined acoustic feature representation	**16**

3.4 Hybrid CNN–LSTM Architecture

To account for spectral and temporal properties of traffic-related acoustic signals a hybrid CNN–LSTM architecture is presented. The complete architecture of the model is illustrated in Fig. 3. For instance, the CNN component learns spectral features from structured acoustic representations, e.g. MFCC feature maps. The operation of convolution is defined as:

The convolution operation used in CNN layers can be expressed as:

$$y(i,j) = \sum_m \sum_n x(i-m, j-n)\, w(m,n) \tag{2}$$

where x represents the input feature map and w represents the convolution kernel.

these feature maps are then transformed into a sequence representation and passed to the LSTM layer. Time dependencies across consecutive observations are captured by the LSTM component, which is used by the model to infer traffic evolution patterns. The LSTM unit input gate is defined as:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

(3)

where x_t is the input vector at time t, h_{t−1} is the previous hidden state, and σ denotes the sigmoid activation function.

Using spectral and temporal features learned, the last output layer predicts estimated traffic congestion state. Of significance, the presented CNN–LSTM architecture is described as a conceptual extension of the more widely used LSTM based classification models and not as an experimental approach. Referring to Fig. 3, we can see that the above hybrid model has convolutional layers for spectral representation learning and LSTM layer for model of the temporal sequence, and dense output layer for congestion prediction. This architecture develops upon the baseline LSTM-based classification paradigm and introduces the model to a more integrated predictive architecture, appropriate for edge based intelligent transportation applications.

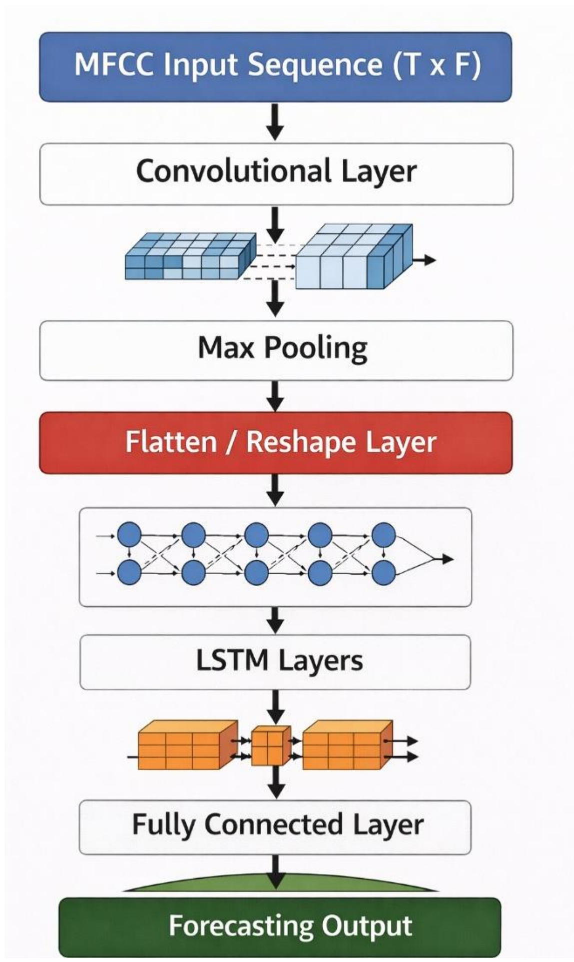

Figure 3. Architecture of the proposed hybrid CNN–LSTM framework for acoustic traffic congestion forecasting.

3.5 Forecasting Formulation and Prediction Strategy

Therefore, conventional acoustic traffic monitoring systems usually define this problem as a classification problem, whereby each acoustic frame is labelled based on the state of the traffic. By contrast, the proposed framework transforms the problem to a time-series forecasting problem. Set X_t to the acoustic feature vector at time t, where a sequence of observations is defined as:

$$S_t = \{X_{t-L+1}, X_{t-L+2}, \ldots, X_t\} \tag{4}$$

where S_t denotes the sliding observation window and L is the sequence length.

The forecasting objective is to estimate the future traffic state at a prediction horizon Δ, which can be expressed as:

$$\hat{Y}_{t+\Delta} = f(S_t) \tag{5}$$

where $\hat{Y}_{t+\Delta}$ represents the forecasted traffic congestion state at prediction horizon Δ.

The above formulation allows the model to adopt historical acoustic observations to estimate future congestion. The forecasting idea is shown conceptually in Fig. 4. In comparison with that, it is expected that long term prediction horizons will lead to significant uncertainties than short prediction horizons, as the traffic system is dynamic. The suggested formulation formulates a structured framework with which to expand acoustic traffic monitoring from a reactive classification into a predictive traffic analysis. The edge computing element has been taken into account at the level of architecture design, while the implementation of the model is not formally implemented.

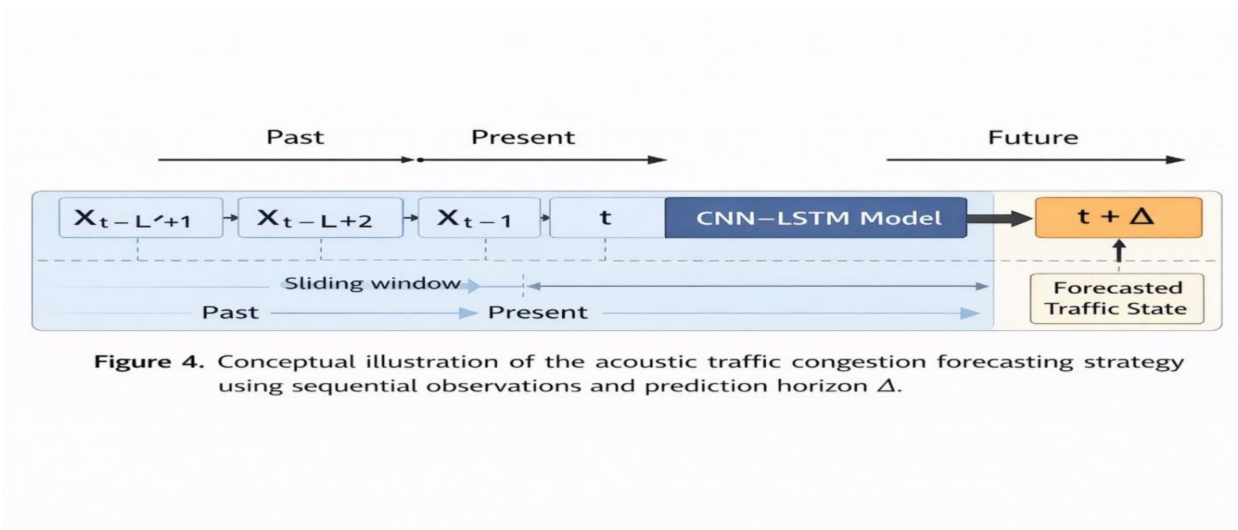

Figure. 4. Conceptual illustration of the forecasting process based on sequential acoustic observations.

4. RESULTS AND DISCUSSION (10 PT)

This section provides theoretical insight into a possible analysis of this acoustic traffic congestion forecasting system, which is based on experimental work previously conducted and a theoretical approach to the proposed architecture. Some existing machine learning and deep learning models have been performed among real-time acoustic traffic datasets including the Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) models, before. Results showed that deep learning methodologies, such as the LSTM-based deep learning, outperformed conventional machine learning in the classification tasks. The LSTM model, in particular, obtains the best performance in the model evaluation by capturing temporal dependencies among acoustic traffic data [16]. These results are a good foundation for the methodological extension suggested here. Given that LSTM models are capable of predicting temporal patterns in traffic-related acoustic signals, extending this capability to the domain of forecasting is a logical step. The proposed framework is based on this premise, and it utilizes convolutional neural networks (CNNs) to improve on the spectral feature learning mechanism, by preserving the feature learning of temporal modelling in the LSTM network. CNN layers are expected to enhance feature characterization by modelling local spectral features that might not be captured as much by solely LSTM-based architectures. This is especially significant for acoustic signals with features from both the frequency-domain as well as temporal patterns that play a role in how traffic conditions are represented. The other main feature of the proposed framework is the shift from classification to forecasting. Traditional acoustic traffic monitoring is not capable of generating outputs beyond recognition of the current state of traffic in conventional traffic monitoring systems. Instead, this particular modeling formulation applies sequential observations to predict future traffic condition results. This move from a reactive to a predictive model is critical for intelligent transportation systems, in which early congestion detection could help promote proactive traffic management. As the prediction horizon increases, the predictive power will decrease due to the randomness in traffic dynamics. In contrast, predictive analysis will be more plausible where the recent temporal trends are closely tied to short-term traffic situation. Besides classification-based evaluation, forecasting models often are evaluated using time-series error metrics, such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).These metrics can deliver a measurable value regarding the gap between predicted and real traffic conditions, which could be instrumental in future studies in order to assess prediction effectiveness. In practical aspects, the proposed framework has a few advantages. The acoustic sensing lessens reliance on costly infrastructure and the edge-based architecture encourages real-time processing with lower latency. Moreover, combining spectral and temporal modeling results in an integrated approach for complex acoustic traffic signals. However, it is also worth mentioning that our framework is conceptualized as an advancement of established experimental data, despite its advantages. Experimental validation of the forecasting model from quantitative performance analysis to comparison with baseline models still serves as a significant direction for future work. Further testing of the proposed framework will involve benchmarking against baseline LSTM models on metrics from the forecasting, MAE and RMSE, on different prediction horizons. It is proposed that a CNN–LSTM approach will build a structured backbone upon which future work can advance acoustic traffic monitoring from a classification approach to a prospective, smart transportation system.

5. CONCLUSION

Here, we propose a conceptual hybrid CNN–LSTM approach for acoustic traffic congestion prediction using low-cost edge computing platforms. This new framework makes use of existing acoustic traffic monitoring methods for prediction of traffic patterns from sequential acoustic data. This work expands on acoustic traffic classification methods that have been validated previously, notably LSTM-based ones, which show promising performance in modeling temporal patterns of traffic related acoustic data. This proposed framework integrates convolutional neural networks for spectral analysis (or spectral feature extraction) along with LSTM networks (for temporal modeling), creating a single framework for spectral and temporal analysis of acoustic signals. One of the contributions of this work is conceptualization of acoustic traffic monitoring as a forecasting and not only classification problem. Such a transition leads to the prediction of traffic congestion states of the future, which is important for a proactive traffic management of intelligent transportation systems. The framework it presents is also developed to accommodate the low-cost nature of edge computing deployments in the real world. While the framework is built on previously validated experimental concepts, it is expected that the full implementation or quantitative analysis of the proposed forecasting model will be conducted in the future. The following study is concentrated on complete experimental implementation such as generation of the required dataset for time-series prediction, model training and estimation of results by relevant forecasting indicators such as MAE and RMSE. The lack of experimental validation is also acknowledged as an issue of the present study.

5.1 FUTURE WORK

Future work will also describe the effect of the prediction horizons in terms of forecasting accuracy, and the architecture optimization of the model for resource-constrained edge devices. Moreover, the incorporation of real-time application and adaptive learning for prediction is a promising path for increasing the relevance of the implementation of acoustic traffic forecasting systems. Overall, the proposed method presents an organized methodological foundation for progressing acoustic traffic monitoring from reactive classification to informed and smart traffic management

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BIOGRAPHIES OF AUTHORS

The recommended number of authors is at least 2. One of them as a corresponding author.
Please attach clear photo (3x4 cm) and vita. Example of biographies of authors:

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