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Smart City Traffic Management: An Ensemble Learning Approach Using Machine Learning

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ABSTRACT:

Efficient traffic management is vital for urban areas, particularly during emergencies where response times can save lives. This study presents a machine learningbased framework for detecting emergency vehicle sounds and improving traffic flow in cities. Acoustic recordings of emergency vehicle sirens are analyzed using advanced feature extraction techniques to identify unique sound patterns. The system employs a stacking ensemble model, combining neural networks to ensure accurate and reliable detection even in noisy urban environments.By integrating with existing traffic management systems, this framework dynamically adjusts traffic signals to prioritize emergency vehicle movement, reducing delays and congestion. The approach not only enhances emergency response times but also contributes to smarter, more efficient urban infrastructure. As cities continue to grow, this system offers a scalable solution to address the challenges of modern traffic management and urban mobility.

Keywords: Emergency Vehicle Detection, Machine Learning, Acoustic Signal Processing , Urban Infrastructure, Traffic Management

INTRODUCTION :-

Managing traffic in modern cities is increasingly challenging due to the rapid growth in the number of vehicles. This results in congestion, delays, and a higher risk of accidents, significantly affecting the quality of life for urban residents. Traditional traffic management systems, which rely on fixed signal timings and manual interventions, are no longer effective as they cannot adapt to real-time traffic conditions. A critical issue in traffic management is ensuring emergency vehicles, such as ambulances and fire trucks, can navigate through congested roads quickly. Delays caused by traffic can have serious, even life-threatening consequences. To address this, ensemble learning models provide a modern solution. These models combine multiple machine learning techniques, like Multi-Layer Perceptrons (MLP), Deep Neural Networks (DNN), and Long Short-Term Memory (LSTM) networks, to make accurate predictions and decisions. By analyzing data from sensors, traffic cameras, and connected vehicles, ensemble models can adjust traffic signals, predict congestion, and prioritize emergency vehicles in real-time. Integrating ensemble learning into traffic management systems helps optimize traffic flow, reduce delays, and create clear paths for emergency response efficiency while supporting sustainable urban infrastructure. Overall, ensemble learning offers a smart and efficient approach to managing urban traffic. It improves mobility, reduces delays, and contributes to creating safer and greener cities, paving the way for smarter urban development.

LITERATURE SURVEY:-

Ullah, I et al.,[1] This study presents a stacking-based ensemble deep learning model to detect emergency vehicle sirens amidst road noise. By combining multiple machine learning models, including Multi-Layer Perceptron (MLP), Deep Neural Networks (DNN), and Long Short-Term Memory (LSTM) networks, the system enhances traffic management in smart cities. The model is designed to improve the prioritization of emergency vehicles, reducing response times and optimizing urban traffic flow. This framework holds significant promise for improving emergency vehicle routing and minimizing delays during critical situations.

Laanaoui, M et al.,[2] This paper introduces a real-time anomaly detection system using a combination of machine learning and big data techniques to address traffic congestion in urban environments. The system utilizes Lambda architecture for batch and stream processing, enabling the analysis of large volumes of data in real-time. The model detects traffic anomalies and disruptions, improving overall traffic flow and helping to prevent accidents. By analyzing real-time data, the system can automatically make adjustments to improve traffic conditions and ensure smoother commutes.

Bindzar, P et al.,[3] This study explores the impact of intersection design on traffic flow during peak hours in urban settings. Using mesoscopic simulations, the authors compare the efficiency of signalized intersections and roundabouts in managing traffic congestion. The study provides valuable

insights into how different intersection designs can improve traffic flow and reduce delays in high-traffic urban areas. These findings can help inform the development of more effective urban road systems to manage growing traffic demands.

Tesone, A et al., [4] This paper proposes a Multiobjective Model Predictive Control (M-MPC) approach to optimize traffic flow and reduce CO2 emissions in urban environments. By using both Urban and Emission Macroscopic Fundamental Diagrams (MFD and e-MFD), the system focuses on balancing traffic efficiency and environmental impact. The model was tested using real-time data from Luxembourg City, demonstrating its effectiveness in improving traffic control strategies and reducing carbon emissions. This approach paves the way for more sustainable traffic management solutions in smart cities.

Guo, R et al., [5] This study examines AI-enabled routing strategies for Connected Autonomous Vehicles (CAVs) in urban areas. By using distributed and decentralized communication methods, the system aims to optimize traffic flow, reduce congestion, and lower emissions. The paper also addresses ethical concerns surrounding the adoption of CAVs, including cybersecurity risks and ensuring equitable access to this technology. The system's integration with smart city infrastructure could transform urban transportation systems by improving efficiency and sustainability while addressing emerging ethical challenges.

Adewopo, V.A et al.,[6] This paper introduces a deep learning ensemble model that combines Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers for traffic accident detection. The model aims to improve traffic safety by enabling faster responses to accidents and optimizing traffic flow. By analyzing real-time traffic data, the system can identify accidents more efficiently and help manage traffic conditions to prevent further incidents, ultimately improving urban traffic management and safety.

Raghunath, K.M et al.,[7] This paper integrates Temporal Convolutional Networks (TCNs) with Federated Learning (FL) to predict traffic patterns and manage urban traffic in a privacy-preserving manner. The model processes data across decentralized sources without centralizing sensitive information, ensuring compliance with privacy regulations. By using TCNs, the system captures temporal dependencies in traffic flow, while FL allows collaborative training across different locations, enabling the system to provide accurate and real-time traffic predictions for smart cities.

Gebre, T.S et al.,[8] This study combines Physics-Informed Neural Networks (PINNs) with GPT-4 for traffic flow prediction and real-time assistance. The model uses physical principles to model and predict traffic dynamics, ensuring accurate and reliable traffic predictions. GPT-4 enables natural language processing to provide real-time, actionable insights for traffic controllers and drivers. This approach enhances the ability to make intelligent, context-aware decisions for dynamic urban traffic management, improving overall traffic flow and efficiency.

Agarwal, I et al.,[9] This paper explores the application of reinforcement learning (RL) in optimizing traffic management systems. By adapting to realtime changes in traffic patterns, RL models improve traffic control, safety, and overall traffic efficiency. The study highlights the potential of RL to address challenges such as congestion, accidents, and the efficient management of traffic lights. The paper also discusses the cybersecurity implications of RL in traffic management systems and the need for secure, scalable solutions for smart cities.

Alruban, A et al.,[10] This paper proposes a hybrid model combining the Artificial Hummingbird Optimization Algorithm (AHOA) and Hierarchical Deep Learning (HDL) for traffic management in Intelligent Transportation Systems (ITS). The AHOA is used to solve complex optimization problems in real-time traffic flow management, while HDL processes traffic data through multiple layers for improved decision-making. The model aims to enhance the efficiency of traffic systems in urban environments by offering optimized solutions for managing traffic flow and improving overall system performance.

Hao, M.-J et al.,[11] This study applies the Greenshields traffic flow theory combined with fuzzy logic to predict traffic congestion on highways. The model predicts congestion patterns with high accuracy and offers a basis for future expansion into urban road scenarios. With IoT sensor integration, the system aims to collect real-time traffic data, enhancing prediction accuracy and allowing for more effective traffic management in dynamic urban environments. This expansion will address the complexity of urban traffic dynamics beyond highways.

Ei Mon, E et al., [12] This paper presents a multi-agent reinforcement learning model for traffic light control in oversaturated urban networks. The model adjusts signal timings in real-time to optimize traffic flow, reduce congestion, and minimize emissions in urban areas. By using decentralized learning, each traffic light can independently make decisions while coordinating with others, creating a more adaptive and responsive traffic management system. Future developments will enhance this model to consider environmental factors, improving sustainability in urban traffic management.

Yang, Y et al.,[13] This paper focuses on optimizing multimodal traffic strategies for emergency evacuations, considering background traffic to improve evacuation efficiency. The system dynamically adjusts traffic management strategies to prioritize emergency vehicle movement and evacuation routes, reducing evacuation times and improving overall flow. By integrating real-time traffic data, the model can adapt to changing conditions, ensuring faster and more efficient evacuations in urban areas during emergencies.

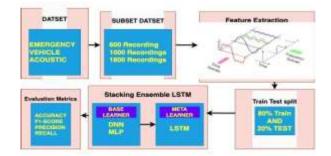
Hazarika, A et al.,[14] The paper introduces an Edge Machine Learning (Edge ML) technique for real-time traffic optimization in smart cities. The approach minimizes latency and enhances scalability by processing data closer to its source. This system optimizes traffic flow in dynamic environments, providing real-time traffic management solutions that are both efficient and adaptive. The Edge ML model ensures that urban traffic systems can scale as cities grow and evolve, offering a scalable solution for future smart city infrastructure.

Cao, Z et al.,[15] This paper presents a simulation model for managing urban traffic flow, integrating regular and connected vehicles. By simulating mixed traffic, the model provides insights into traffic dynamics and helps optimize traffic flow in urban areas. The approach considers interactions

between traditional vehicles and connected vehicles, offering strategies to improve traffic management and reduce congestion in cities with diverse traffic environments. Future work includes integrating real-time simulation capabilities for adaptive traffic management.

METHODOLOGY:

This study presents a framework for detecting emergency vehicle sirens in smart cities, using deep learning techniques to identify sirens in real-time amidst urban noise. The system combines feature extraction, ensemble learning models, and scalable strategies to tackle noise interference and environmental challenges. By enabling faster emergency response times and reducing traffic congestion, it improves traffic management. The modular design ensures compatibility with various urban environments, and real-time classification allows immediate traffic signal adjustments for emergency vehicles.



Data Collection and Preprocessing

The dataset consists of 1800 audio recordings from Karachi, Pakistan, containing both emergency sirens and road noises. Microphone sensors captured high-fidelity audio, sampled at 22 kHz and upsampled to 44.1 kHz for better clarity. Preprocessing included noise reduction, audio level normalization, and segmentation into consistent timeframes for analysis. The dataset was divided into three subsets to evaluate the model's scalability: 600, 1000, and 1800 recordings.

Feature Engineering and Selection

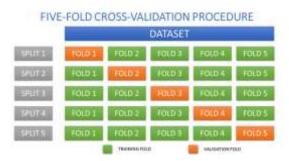
Key features, such as Mel Frequency Cepstral Coefficients (MFCCs), Zero-Crossing Rate (ZCR), and Root Mean Square (RMS), were extracted to differentiate sirens from background noise. These features were selected using domain knowledge and statistical techniques. Redundant features were removed to reduce overfitting, and synthetic data generation techniques helped improve the model's generalization.

Stacking-Based Ensemble Learning

The core of the methodology is a stacking-based ensemble learning framework, which integrates multiple deep learning models. The base models include Multi-Layer Perceptron (MLP) for high-level feature patterns and Deep Neural Networks (DNN) for extracting spatial attributes from audio signals. The meta-learner is Long Short-Term Memory (LSTM), which processes sequential data to capture temporal relationships in sound patterns. The model combines the predictions of these models to improve accuracy and robustness.

Model Training and Cross-Validation

The model underwent extensive training using a 5-fold cross-validation approach, ensuring robustness and minimizing bias. Hyperparameters, including learning rates and activation functions, were optimized for the best performance. Performance was evaluated using accuracy, precision, recall, F1 scores, and confusion matrices to assess the model's reliability.



Acoustic Signal Processing for Real-Time Detection

The system continuously monitors acoustic signals using microphone sensors deployed in traffic-heavy areas. The extracted features, such as MFCCs and RMS, are processed in real-time to detect emergency sirens. Once a siren is detected, the system triggers adaptive traffic responses, such as adjusting traffic signals, with minimal latency to ensure quick emergency vehicle passage.

Integration and Scalability

The system is designed to integrate easily with existing smart city infrastructure and can be scaled to cover larger areas by adding more sensors and computing units. It is also compatible with IoT devices like connected cameras and vehicle sensors, forming a comprehensive smart traffic network. The model can adapt to various urban environments, trained on diverse datasets to handle different noise profiles and traffic conditions.

RESULTS:-

This study applied a stacked ensemble deep learning model, combining MLP, DNN, and LSTM, to detect emergency vehicle sirens in real-time from road noise. The model was evaluated on three subsets of audio data: 1800, 1000, and 600 audio recordings. The overall performance of the stacked ensemble model was strong, with significant improvements over previous models in emergency vehicle detection. The integration of multiple deep learning models allowed the system to capture complex acoustic patterns, leading to more accurate and reliable identification of emergency sirens amidst urban noise, making it highly suitable for smart city traffic management.

- Accuracy: The model achieved 99.12% accuracy across all test datasets, outperforming previous studies.
- Precision and Recall: The Precision-Recall F1 scores ranged from 98% to 100%, showing the model's ability to accurately differentiate sirens from road noise.
- Feature Engineering: Advanced features like MFCC, spectral flux, and RMS played a crucial role in the model's success by capturing key differences in urban sounds and emergency vehicle sirens.
- Dataset Variability: Tests using different subsets (1800, 1000, and 600 recordings) showed that the stacked LSTM model consistently
 outperformed the DNN and MLP models in all cases.

Performance on 1800 Audio Subset:

• The LSTM model achieved 98.56% accuracy, with MLP and DNN models following at 99% and 97.5%, respectively.

Performance on 1000 Audio Subset:

• The MLP model achieved 99% accuracy, while the LSTM model slightly outperformed it at 99.12%. The DNN model achieved 98.54%.

Performance on 600 Audio Subset:

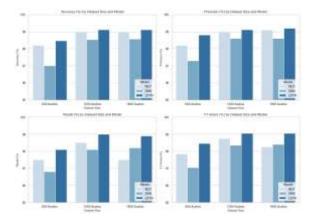
• The LSTM model achieved the highest accuracy of 98.46%, followed by the MLP and DNN models at 98.2% and 97%, respectively.

The proposed acoustic-based vehicle detection model demonstrated high accuracy across all datasets:

- 98.12% accuracy with 1000 audio recordings.
- 97.56% accuracy with 1800 audio recordings.
- 97.46% accuracy with 600 audio recordings.

The **LSTM model** consistently showed the highest precision and recall across the datasets, with 100% precision on the 1000 audio recordings dataset. The **F1-Score** remained high across datasets, with LSTM achieving 98% for all subsets.

These results highlight the model's strong ability to accurately identify emergency vehicle sirens in complex urban environments, making it a reliable solution for improving emergency vehicle prioritization in smart city traffic systems. The system's high accuracy ensures timely emergency response and reduces traffic congestion, contributing to safer, more efficient urban transportation.



CONCLUSION:

The results of this study demonstrate the transformative potential of using a stacked ensemble deep learning approach for smart city traffic management. By combining LSTM, DNN, and MLP models, the system achieves robust real-time classification of emergency vehicle sirens, even in complex urban environments. With an accuracy of 99.12%, this technology shows significant promise for addressing the critical need to clear traffic for emergency vehicles efficiently, potentially reducing response times and saving lives.

The integration of this system into existing smart city infrastructure enables dynamic traffic signal adjustments, ensuring emergency vehicles can navigate congested roads quickly. Additionally, by optimizing traffic flow, the system minimizes disruptions for regular vehicles while enhancing overall urban mobility. These capabilities pave the way for smarter, more responsive traffic management solutions. This study provides a strong foundation for future advancements in automated emergency response technologies. Future work can focus on expanding the system's capabilities, such as integrating multi-modal data sources and improving noise resilience, to further enhance its performance in real-world scenarios. By contributing to the vision of fully integrated smart city systems, this research represents a valuable step toward creating safer, more efficient urban environments for all.

REFERENCES:

[1] A. Alruban, H.A. Mengash, M.M. Eltahir, N.S.Almalki, A. Mahmud and M. Assiri, "Artificial Hummingbird Optimization Algorithm With Hierarchical Deep Learning for Traffic Management in Intelligent Transportation Systems," in IEEE Access, vol. 12, pp. 17596-17603, 2024, doi: 10.1109/ACCESS.2023.3349032

[2] A. Hazarika, N. Choudhury, M. M. Nasralla, S. B. A. Khattak and I. U. Rehman, "Edge ML Technique for Smart Traffic Management in Intelligent Transportation Systems," in IEEE Access, vol. 12, pp. 25443-25458, 2024, doi: 10.1109/ACCESS.2024.3365930

[3]A. Shabbir, A. N. Cheema, I. Ullah, I. M. Almanjahie and F. Alshahrani, "Smart City Traffic Management: Acoustic-Based Vehicle Detection Using Stacking-Based Ensemble Deep Learning Approach," in IEEE Access, vol. 12, pp. 35947-35956, 2024, doi: 10.1109/ACCESS.2024.3370867

[4]A. Tesone, T. Tettamanti, B. Varga, G. N. Bifulco and L. Pariota, "Multiobjective Model Predictive Control Based on Urban and Emission Macroscopic Fundamental Diagrams," in IEEE Access, vol. 12, pp. 52583-52602, 2024, doi: 10.1109/ACCESS.2024.3387664

[5] Cao, L., L. Lu, C. Chen and X. Chen, "Modeling and Simulating Urban Traffic Flow Mixed With Regular and Connected Vehicles," in IEEE Access, vol. 9, pp. 10392-10399, 2022, doi: 10.1109/ACCESS.2021.3050199

[6]E. Ei Mon, H. Ochiai and C. Aswakul, "Application of Traffic Light Control in Oversaturated Urban Network Using Multi-Agent Deep Reinforcement Learning," in IEEE Access, vol. 12, pp. 82384-82395, 2024, doi: 10.1109/ACCESS.2024.3397495

[7] **I. Agarwal** et al., "Enhancing Road Safety and Cybersecurity in Traffic Management Systems: Leveraging the Potential of Reinforcement Learning," in IEEE Access, vol. 12, pp. 9963-9975, 2024 [8]

[8]K. M. Karthick Raghunath et al., "Redefining Urban Traffic Dynamics With TCN-FL Driven Traffic Prediction and Control Strategies," in IEEE Access, vol. 12, pp. 115386-115399, 2024, doi: 10.1109/ACCESS.2024.3443298

[9] M. Driss Laanaoui, M. Lachgar, H. Mohamed, H. Hamid, S. Gracia Villar and I. Ashraf, "Enhancing Urban Traffic Management Through Real-Time Anomaly Detection and Load Balancing," in IEEE Access,vol. 12, pp. 63683-63700, 2024, doi: 10.1109/ACCESS.2024.3393981

[10]**M. J. Hao** and B. -Y. Hsieh, "Greenshields Model-Based Fuzzy System for Predicting Traffic Congestion on Highways," in IEEE Access, vol. 12, pp. 115868-115882, 2024, doi: 10.1109/ACCESS.2024.3446843

[11] **P. Bindzar**, D. Marasova, J. Brodny, M. Tutak, R. Ulewicz and A. Sliva, "Modeling the Impact of Intersection Design Configurations on Traffic Flow During Peak Hour in Smart Cities: A Case Study on Urban Roads in Slovakia," in IEEE Access, vol. 12, pp. 83072-83090, 2024, doi: 10.1109/ACCESS.2024.3412709

[12] **R. Guo**, M. Vallati, Y. Wang, H. Zhang, Y. Chen and F. -Y. Wang, "Sustainability Opportunities and Ethical Challenges of AI-Enabled Connected Autonomous Vehicles Routing in Urban Areas," in IEEE Transactions on Intelligent Vehicles, vol. 9, no. 1, pp. 55-58, Jan. 2024, doi: 10.1109/TIV.2023.3345661

[13]**T. Syum Gebre**, L. Beni, E. Tsehaye Wasehun and F. Elikem Dorbu, "AI-Integrated Traffic Information System: A Synergistic Approach of Physics Informed Neural Network and GPT-4 for Traffic Estimation and Real-Time Assistance," in IEEE Access, vol. 12, pp. 65869-65882, 2024, doi: 10.1109/ACCESS.2024.3399094

[14]**V. A. Adewopo** and N. Elsayed, "Smart City Transportation: Deep Learning Ensemble Approach for Traffic Accident Detection," in IEEE Access, vol. 12, pp. 59134-59147, 2024, doi: 10.1109/ACCESS.2024.3387972

[15]**Y. Yang**, T. Zhang, Q. Jia, G. Cheng, Q. Yu and M. Jin, "Optimal Design of Multimodal Traffic Strategies in Emergency Evacuation Considering Background Traffic," in IEEE Access, vol. 10, pp. 77158-77169, 2022, doi: 10.1109/ACCESS.2022.3193145