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CONGESTION-PRONE POINT CLASSIFICATION SYSTEM USING SOM METHOD ANDROID-BASED

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ABSTRACT

Urban traffic congestion has emerged as a significant challenge, primarily driven by rapid urban expansion and increasing vehicle usage. This study presents the development of a congestion-prone point classification system utilizing the Self-Organizing Maps (SOM) algorithm, integrated into an android-based mobile application. The primary objective is to facilitate the real-time detection and visualization of traffic density hotspots using unsupervised machine learning techniques. Traffic-related data comprising vehicle volume, type distribution, and geospatial coordinates are systematically collected, preprocessed, and transformed into multidimensional feature vectors. These vectors are processed using the SOM algorithm to uncover latent congestion patterns across various road segments. Testing results indicate that the proposed model is capable of accurately identifying congestion-prone areas, which are subsequently visualized within the mobile application using a colour-coded map interface. This integration provides commuters and traffic management authorities with actionable, data-driven insights to support route optimization and congestion alleviation strategies. Overall, the proposed system contributes to the advancement of intelligent transportation infrastructure within the broader framework of smart city development.
Keywords: *Traffic Congestion, Self-Organizing Map, Android Application, Smart City, Unsupervised Learning, Geospatial Data*

ABSTRAK

Kemacetan lalu lintas pada wilayah perkotaan telah menjadi tantangan krusial yang dipicu oleh pesatnya ekspansi perkotaan dan meningkatnya jumlah kendaraan. Penelitian ini menyajikan pengembangan sistem klasifikasi titik rawan kemacetan menggunakan algoritma Self-Organizing Maps (SOM), yang diintegrasikan ke dalam aplikasi mobile berbasis android. Tujuan utama dari penelitian ini adalah untuk memfasilitasi deteksi dan visualisasi waktu nyata terhadap titik-titik kepadatan lalu lintas melalui teknik machine learning tanpa supervisi. Data lalu lintas yang mencakup volume kendaraan, distribusi tipe kendaraan, dan koordinat geospasial dikumpulkan secara sistematis, dipraolah, dan diubah menjadi vektor fitur multidimensi. Vektor-vektor ini kemudian diproses oleh algoritma SOM untuk mengungkap pola laten kemacetan pada berbagai segmen jalan. Hasil pengujian menunjukkan bahwa model yang diusulkan mampu mengidentifikasi area rawan kemacetan secara akurat, yang selanjutnya divisualisasikan melalui antarmuka pemetaan berwarna dalam aplikasi mobile. Integrasi ini memberikan wawasan berbasis data yang dapat ditindaklanjuti bagi pengguna jalan dan otoritas lalu lintas dalam upaya optimalisasi rute dan mitigasi kemacetan. Secara keseluruhan, sistem yang diusulkan berkontribusi terhadap pengembangan infrastruktur transportasi cerdas dalam kerangka pembangunan kota cerdas.
Kata Kunci: Kemacetan Lalu Lintas, Self-Organizing Map, Aplikasi Android, Kota Pintar, Unsupervised Learning, Data Geospasial.

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INTRODUCTION

Urban traffic congestion presents a significant and escalating challenge, exacerbated by rapid urban expansion and the increasing prevalence of private vehicle ownership [1]. These conditions contribute to persistent traffic bottlenecks, particularly in areas characterized by inadequate infrastructure and widespread illegal parking practices. The resulting disruptions to traffic flow not only impede urban mobility but also intensify environmental degradation an issue that reflects broader patterns observed in many metropolitan centres globally [2].

Despite ongoing traffic management efforts, existing systems in Makassar lack the analytical sophistication required to classify congestion-prone areas based on dynamic and multidimensional traffic indicators. This shortcoming limits the ability of traffic authorities to deploy targeted interventions and make real-time, data-informed decisions [3] [4]. Infrastructural determinants, such as intersection density and the absence of formal parking zones, further intensify congestion along critical corridors, underscoring the need for analytical tools capable of capturing and interpreting these spatial complexities [5] [6].

To address these challenges, this study proposes the development of a congestion-prone point classification system utilizing the SOM algorithm [7]. SOM is a robust unsupervised machine learning technique known for its ability to process high-dimensional datasets and map them into lower-dimensional topologies that reveal latent spatial and temporal patterns [8]. The objective of this research is to facilitate the real-time identification and geospatial visualization of traffic congestion zones by incorporating key variables, including traffic volume, vehicle composition, temporal fluctuations, and positional data. These outputs will be integrated into an Android-based mobile application, designed to provide traffic management authorities and urban commuters with actionable insights to optimize routing, inform infrastructure planning, and implement effective congestion mitigation strategies [9] [10].

The integration of intelligent transportation systems into urban traffic governance has shown considerable promise in enhancing operational efficiency and supporting long-term sustainability goals. Recent studies have highlighted the transformative potential of artificial intelligence (AI) in advancing real-time traffic management, particularly through applications in routing optimization and congestion prediction [11]. As urban environments continue to confront the compounded pressures of population growth, vehicular demand, and environmental degradation, innovative frameworks that leverage machine learning and real-time analytics are essential. Developing such data-driven solutions is pivotal to realizing sustainable, adaptive, and intelligent urban transport systems [12].

This study introduces a SOM-based framework to classify congestion-prone areas in Makassar City using multidimensional traffic data. It enables real-time detection and visualization of traffic hotspots by integrating traffic volume, vehicle types, temporal patterns, and geospatial attributes. The model is deployed in an Android-based mobile application to provide practical support for commuters and traffic authorities. This research contributes to intelligent transportation systems by promoting data-driven urban mobility management, offering a scalable solution applicable to other urban contexts.

METHOD

Data Collection

The data collection phase serves as a critical foundation for the successful implementation of the Self-Organizing Map (SOM) classification system in this study. The primary data types collected include:

a. Traffic Volume Data

This dataset captures the number of vehicles passing through specific road segments over a defined period. It serves as a key indicator of traffic density and is essential for identifying peak and off-peak congestion levels.

b. Vehicle Type Distribution

Data on the types of vehicles helps assess the impact of different vehicle classes on congestion. This information supports clustering road segments with distinct traffic compositions.

c. Geospatial Coordinates (GPS Data)

Each traffic record is tagged with latitude and longitude coordinates to enable precise spatial mapping of congestion-prone points within the city.

All collected data are structured into feature vectors suitable for input into the SOM algorithm. Prior to model training, the data undergo preprocessing steps including normalization, noise filtering, and dimensional alignment. The resulting dataset serves as the basis for unsupervised clustering, enabling the identification of congestion-prone areas that reflect both the spatial and temporal dynamics of urban traffic in Makassar.

Android Operation System

The Android operating system, based on the Linux kernel, has rapidly become the most widely used mobile OS globally due to its open-source nature [13], enabling extensive flexibility and customization for developers and users alike [14]. Initiated by Google, Android integrates middleware and various applications within its environment, allowing developers to create a multitude of applications, which significantly contributes to its popularity [15]. The operating system's open architecture not only appeals to users but also fosters a vast ecosystem of applications that can be tailored for different devices and user needs [16]. As of 2021, Android dominated the mobile operating system market, boasting an estimated 80% share among smartphone users, significantly outpacing its closest rival, Apple's iOS [17]. The growth of Android has been propelled by major companies integrating this OS into their devices, with over 2.8 billion active users by 2021 [18]. This expansive reach into various demographic segments underscores Android's accessibility, particularly in regions such as Southeast Asia, where it reportedly holds market shares upwards of 89% in some areas as of late 2022 [19].

However, with such widespread adoption comes heightened security risks. Android devices are frequent targets for malware, including viruses, Trojans, and ransomware, leading to significant vulnerabilities for users [20]. Malware targeting the Android operating system can affect countless users due to the diverse range of applications and services running on these devices. Reports indicate that nearly half of Android malware is multifunctional Trojans, commonly designed to steal sensitive personal information [21]. In response to the growing threat landscape, various detection methodologies, such as machine learning, have been proposed to combat these malicious activities effectively [22]. The Android operating system stands as a leading mobile platform characterized by its extensive user base and flexibility for developers.

Self-Organizing Maps (SOM)

Self-Organizing Maps represent a prominent unsupervised learning technique within neural networks, particularly useful for dimensionality reduction and clustering in various fields of study. The development of SOM, introduced by previous research, enables the mapping of high-dimensional data into a low-dimensional, typically two-dimensional, space while preserving topological properties [23]. This mapping operates through a competitive learning mechanism that allows each node to adaptively respond to input data based on similarity, thus forming clusters. SOM are particularly effective in handling multidimensional data, finding extensive applications in areas such as climatology, epidemiology, and socio-economic studies. For instance, they have been used to analyze complex weather patterns, revealing intrinsic data structures by projecting weather-related variables into a manageable visual format [24].

Moreover, the adaptability of SOM is well-documented in the literature. They have been integrated with various clustering techniques, enhancing their utility. Comparisons with methods like fuzzy c-means have demonstrated the effectiveness of SOM in specific contexts [25]. The self-organizing mechanism allows for an intuitive and interpretable clustering outcome, which is a significant advantage for exploratory data analysis [26]. Researchers have illustrated that employing SOM, alongside complementary methods, can yield informative clusters that can

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facilitate decision-making processes in diverse sectors, from healthcare to urban planning [27]. In recent advancements, researchers are also focusing on enhancing the robustness and efficiency of SOM. Techniques such as integrating SOM with genetic algorithms for portfolio optimization underline their versatility and applicability across different domains [28].

The core principle of the SOM algorithm is the gradual reduction of influence from neighboring nodes. Ultimately, only a single output node is selected as the winner node. The SOM algorithm operates through the following steps [29]:

i. Initialize the weight vectors and the learning rate α.
ii. Repeat the following steps until the stopping condition is met:
   a) For each input vector **x**, perform the following:
   b) For each output node j, calculate the distance:

$$D_j = \sum_j (w_{ji} - x_j)^2 \qquad (1)$$

   c) Identify the index j with the smallest D_j value — this is the winner node.
   d) Update the weights of the winner node and its neighbors using the formula:

$$w_{ij}^{\text{new}} = w_{ij}^{\text{old}} + \alpha(x_i - w_{ij}^{\text{old}}) \qquad (2)$$

where w = weight vector, α = learning rate $0 < \alpha(t) < 1$, x = input vector, i = index of input node, and j = index of output node.

iii. Update the learning rate α over time.
iv. Reduce the neighborhood radius as learning progresses.
v. Check if the stopping condition is met.

SOM method demonstrates a profound potential as a versatile tool for clustering and dimensionality reduction in various fields.

Framework Proposed

To systematically address the issue of traffic congestion, this study adopts a framework that integrates intelligent data processing and mobile-based visualization, as illustrated in Figure 1.

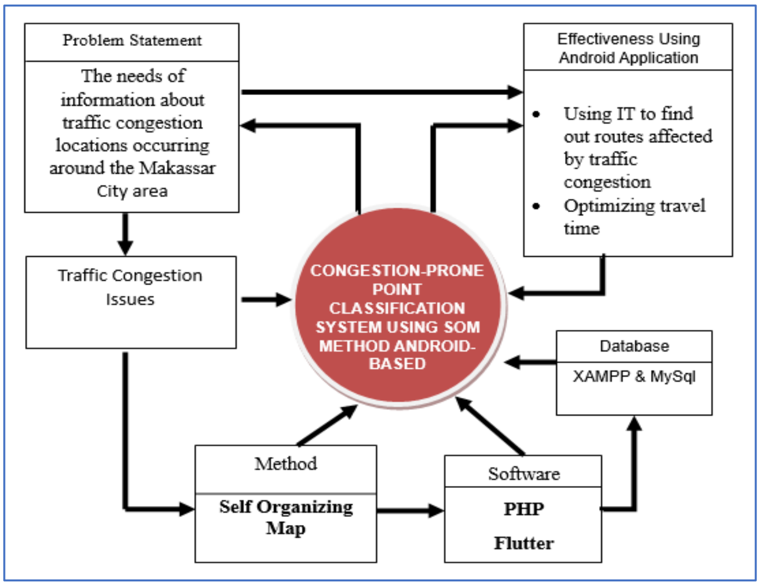

Figure 1. Framework Proposed

The adoption of a SOM-based traffic classification framework represents an innovative and systematic strategy to address persistent congestion challenges. By capturing the multifaceted dimensions of urban mobility patterns, this approach facilitates evidence-based decision-making and long-term improvements in traffic flow, ultimately contributing to a more sustainable and efficient urban transportation system.

RESULTS AND DISCUSSION

Implementation of The SOM Method

The simulation results were validated to ensure that the model did truly described the actual system conditions. The verification process was conducted by checking the model and unit using the facilities available in Vensim. System validation can be carried out in two ways: model validation with mean comparison test statistics, or model validation with amplitude variation comparison tests or percentage error variance [30].

To demonstrate the working mechanism of the SOM algorithm in the proposed congestion-prone classification system, a simplified case scenario is implemented. This simulation reflects the process of classifying traffic condition vectors into predefined clusters using SOM logic, which is later integrated into the Android-based application for real-time classification of road congestion in Makassar City. The process of applying the SOM method involves several features, including, firstly, the Speed variable, which contains the average speed of the vehicle at that point (km/h). Secondly, the Vehicle Count variable, which contains the average number of vehicles per hour as simulated by a loop detector sensor. Thirdly, Road Width variables contain the road width in meters. Fourthly, Signal Delay loads the length of the waiting time at the red light in seconds. Lastly, Intersections contains the number of intersections within a given radius of the point. The Dataset used in this study is shown in Table 1.

Table 1. Dataset Collected

Point	Speed	Vehicle Count	Road Width	Signal Delay	Intersections
P1	10	2200	5	85	3
P2	35	1000	10	30	1
P3	20	1500	6	60	2
P4	8	2600	5	90	4
P5	40	800	12	25	1
P6	12	1800	7	70	3
P7	18	1700	6	75	2
P8	28	1300	8	45	2
P9	6	2700	4	95	5
P10	32	900	11	35	1
P11	15	2000	6	80	3
P12	22	1400	7	55	2
P13	5	2800	4	100	5
P14	30	1100	9	40	1
P15	25	1600	8	50	2
P16	7	2500	5	88	4
P17	14	1900	6	78	3

Based on the data in Table 1, the data update process is carried out by calculating the Euclidean distance between the data and each neuron. It is followed by determining the best matching unit based on the neurons with the closest distance. The results of the calculation in iteration 1 are shown in Table 2.

Table 2. Calculation Result of Updating Neuron

Neurons	Speed	Vehicle	Width	Delay	Intersections
Neuron 0 (Before)	0.3745	0.9507	0.732	0.5987	0.156
Neuron 0 (After)	0.1873	0.9754	0.366	0.7993	0.578
Neuron 1 (Before)	0.156	0.0581	0.8662	0.6011	0.7081
Neuron 1 (After)	0.578	0.029	0.9331	0.3006	0.354

Illustration of the calculation of neuron value update on feature speed using written values$\alpha = 0.5$:

$$w_{Speed}^{new}=0.3745 + 0.5\ (0.143 - 0.3745) = 0.3745 - 0.11575 = 0.259$$

The overall calculation results are shown in Table 3.

Table 3. Calculation Results of Update Feature

Feature	Old Weight	Input	New Weight
Speed	0.3745	0.143	0.259
Vehicle	0.9507	0.75	0.850
Width	0.7320	0.167	0.4495
Delay	0.5987	0.857	0.7279
Intersections	0.1560	0.5	0.328

Each road segment's data is encoded into a vector and processed using the trained SOM model. The resulting classification assigns the segment to a specific congestion-prone cluster. Comparison between the Co-Prone Location application and the actual situation in front of Warkop 27 Alauddin street, as shown in Figures 2 and 3.

Figure 2. Comparison of applications on Smooth traffic conditions

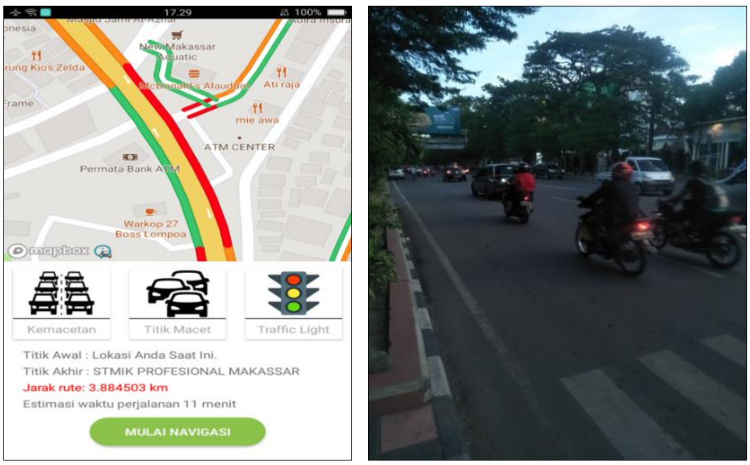

Figure 3. Comparison of Applications in Traffic Jam situations

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The Android application then fetches this classification and visualizes it using color-coded maps:

- Low congestion
- Moderate congestion
- High congestion

This implementation enables the system to dynamically learn and adapt to new traffic patterns, providing users with up-to-date congestion levels and supporting proactive navigation decisions for commuters.

The results and discussion of this study demonstrate the effective implementation of the Self-Organizing Maps method in classifying congestion-prone areas in Makassar City. By processing normalised traffic data, which includes average vehicle speed, vehicle count, road width, signal delay, and intersection density, the SOM algorithm calculates Euclidean distances to determine the best matching unit for each data point, followed by weight updates using a learning rate of 0.5. The simulation, conducted at 17 traffic points, validates the model’s ability to adapt to real-world traffic patterns through accurate adjustments to neuron weights. The classification results categorize traffic conditions into low, moderate, and high congestion levels, which are visualized in real-time through an Android-based application using a colour-coded map interface. A comparative test case near Warkop 27, Jalan Alauddin, supports the accuracy of the application’s output by aligning well with actual traffic observations. Overall, the SOM-based system proves to be a reliable, adaptive, and practical tool for real-time congestion monitoring, offering valuable support for both commuters and traffic authorities in making informed navigation and planning decisions.

CONCLUSION

This research demonstrates that the application of the Self-Organizing Map (SOM) algorithm in classifying congestion-prone areas provides a practical and scalable solution to traffic management challenges in Makassar City. By processing key features such as traffic volume, vehicle composition, and temporal flow, the SOM model successfully clusters urban road segments based on congestion severity. When integrated into an Android-based application, the system provides a user-friendly, real-time visualization tool for both users and traffic authorities. The case simulation confirmed the algorithm's ability to adapt and classify traffic data dynamically. Overall, this approach provides a data-driven and user-oriented framework to support route optimization, infrastructure planning, and proactive traffic mitigation strategies, ultimately contributing to more sustainable urban transportation systems.

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