

# EVALUATING DIFFERENT ALGORITHMS FOR REAL-TIME TRAFFIC ANALYSIS

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**ABSTRACT:** *This study compares the performance of three machine learning algorithms—Algorithm A, Algorithm B, and Algorithm C—across multiple metrics encompassing classification accuracy, precision, recall, F1 score, AUC-ROC, regression MSE, R-squared, and real-time processing capabilities (throughput and latency). Results show Algorithm B excels in classification tasks with the highest accuracy (0.87) and precision (0.88), while Algorithm C achieves superior recall (0.91). Algorithm A demonstrates robust performance in AUC-ROC (0.91) among classifiers. In regression, Algorithm B exhibits the lowest MSE (0.10) and highest R-squared (0.82), indicating accurate and explanatory predictive capabilities. Algorithm C proves efficient in real-time scenarios with the highest throughput (5100 ops/sec) and lowest latency (18 ms). These findings offer insights into algorithm selection tailored to specific application requirements.*

## INTRODUCTION

Real-time traffic analysis is a crucial component of modern transportation management systems, encompassing the continuous monitoring, interpretation, and prediction of traffic conditions as they unfold. Leveraging advanced technologies such as sensors, cameras, GPS data, and communication networks, real-time traffic analysis aims to provide timely and accurate insights into traffic flows, congestion levels, and incident detection on road networks. This capability is essential for improving the efficiency of transportation systems, enhancing safety, reducing travel times, and minimizing environmental impact.

In urban environments, where traffic congestion is a persistent challenge, real-time traffic analysis plays a pivotal role in optimizing traffic flow and mitigating bottlenecks. By collecting and analyzing data from various sources in real-time, transportation authorities and planners can make informed decisions to manage traffic signals dynamically, adjust lane configurations, or divert traffic to alternative routes. This proactive approach not only improves the overall traffic flow but also enhances the responsiveness of emergency services and facilitates smoother movement of goods and services.

Moreover, real-time traffic analysis supports the development of intelligent transportation systems (ITS), which integrate data-driven insights with automated control systems. These systems enable adaptive strategies such as predictive traffic modeling, where algorithms anticipate future traffic conditions based on historical data patterns and current observations. By preemptively adjusting traffic management strategies, ITS can preemptively mitigate potential congestion hotspots and optimize resource allocation.

The importance of real-time traffic analysis extends beyond urban areas to encompass broader regional and inter-city transportation networks. By monitoring traffic conditions across highways, toll roads, and major transit corridors, transportation agencies can optimize toll pricing, manage lane usage efficiently, and enhance the overall travel experience for commuters and long-distance travelers alike. This capability is particularly critical during peak travel periods and major events, where rapid changes in traffic volume and patterns necessitate immediate intervention and adaptive management strategies.

Furthermore, real-time traffic analysis supports data-driven policymaking and infrastructure planning. By providing comprehensive traffic insights, including origin-destination patterns, traffic densities, and travel behavior trends, decision-makers can prioritize investments in transportation infrastructure, allocate resources effectively, and evaluate the impact of policy interventions. This evidence-based approach not only enhances the resilience of transportation systems but also contributes to sustainable urban development by promoting multimodal transport solutions and reducing reliance on private vehicle travel.

Using different algorithms for real-time traffic analysis is significant due to several compelling reasons rooted in the complexities and dynamic nature of traffic management and optimization. These algorithms are instrumental in processing vast amounts of real-time data efficiently, extracting meaningful insights, and enabling timely decision-making in transportation systems.

Firstly, the diversity of algorithms allows for tailored approaches to handling various aspects of traffic analysis. Machine learning algorithms, for instance, excel in recognizing patterns and anomalies within traffic data, which is crucial for predicting congestion or identifying unusual traffic behavior indicative of accidents or incidents. Statistical algorithms, on the other hand, are adept at modeling traffic flow dynamics and probabilistic forecasting,

providing probabilistic estimates of travel times and congestion levels based on historical trends and current data.

Secondly, the scalability of algorithms is essential in managing large-scale transportation networks. Real-time traffic analysis often involves processing data from numerous sensors, cameras, and connected vehicles spread across extensive urban or regional areas. Algorithms capable of distributed computing, parallel processing, or efficient data aggregation are vital for handling the volume and velocity of data generated continuously in such environments. These capabilities ensure that transportation authorities can monitor and respond to traffic conditions promptly across vast networks.

Moreover, the adaptability of algorithms is crucial in addressing the diverse and evolving challenges of traffic management. Traffic patterns can vary significantly by time of day, day of the week, or due to special events. Algorithms that can adaptively learn from new data, adjust parameters dynamically, or incorporate real-time feedback mechanisms enable transportation systems to respond flexibly to changing conditions. This adaptability is particularly valuable in dynamic environments where traditional static control methods may be insufficient.

Furthermore, the accuracy of algorithms directly impacts the effectiveness of traffic management decisions. Algorithms capable of leveraging diverse data sources and integrating complex variables (such as weather conditions, road incidents, and public events) into their models can provide more accurate predictions and recommendations. High accuracy is crucial for optimizing traffic flow, minimizing delays, and improving the reliability of travel time estimates, thereby enhancing user satisfaction and operational efficiency.

Additionally, the efficiency of algorithms plays a critical role in ensuring real-time responsiveness in traffic management systems. Real-time traffic analysis requires algorithms that can process incoming data streams rapidly, compute results swiftly, and disseminate actionable insights to decision-makers and automated control systems within minimal latency. Efficient algorithms facilitate timely interventions such as adjusting traffic signal timings, rerouting vehicles, or deploying emergency response services, thereby mitigating potential congestion or improving incident management.

The objectives of research focusing on evaluating different algorithms for real-time traffic analysis are multifaceted, aiming to address several critical aspects of transportation management and optimization. These objectives are designed to contribute new insights, methodologies, and practical solutions to enhance the efficiency, safety, and reliability of urban and regional transportation systems.

Firstly, one primary objective is to **compare the performance** of various algorithms used in real-time traffic analysis. This involves systematically evaluating different algorithmic approaches, such as machine learning models (e.g., neural networks, decision trees), statistical methods (e.g., time series analysis, Bayesian networks), and hybrid techniques (e.g., ensemble learning), across key metrics. Metrics may include accuracy in predicting traffic patterns, robustness in handling diverse data sources, scalability to large-scale networks, and computational efficiency. By comprehensively assessing algorithmic performance, the research aims to identify strengths and weaknesses relative to specific application scenarios and operational requirements.

Secondly, the research seeks to **validate algorithmic effectiveness** through empirical analysis using real-world datasets. This objective involves acquiring and preprocessing diverse datasets encompassing traffic flow data, incident reports, weather conditions, and demographic information. These datasets are crucial for training and testing algorithms under realistic conditions, reflecting the variability and complexity of urban traffic environments. The validation process includes conducting controlled experiments, cross-validation techniques, and comparative analyses to ascertain the reliability and generalizability of algorithmic predictions and recommendations.

Another key objective is to **explore algorithmic adaptability** to dynamic traffic conditions and evolving urban landscapes. This involves investigating algorithms capable of adaptive learning, real-time updating, and responsiveness to sudden changes in traffic patterns or external factors (e.g., accidents, road closures, special events). The research aims to highlight algorithms that can dynamically adjust their models, parameters, or decision-making criteria based on incoming data streams, thereby enhancing the agility and effectiveness of traffic management strategies.

Furthermore, the research endeavors to **contribute to algorithmic innovation** by proposing novel enhancements or hybridizations of existing approaches. This objective includes

exploring interdisciplinary insights from fields such as computer science, transportation engineering, and data analytics to develop innovative algorithmic frameworks. Examples may include integrating sensor fusion techniques, leveraging advanced predictive analytics, or optimizing algorithmic architectures for distributed computing environments. Such innovations aim to push the boundaries of current algorithmic capabilities in real-time traffic analysis, fostering more accurate, adaptive, and scalable solutions for transportation stakeholders.

Additionally, the research aims to **inform evidence-based decision-making** and policy formulation in transportation management. By providing clear, actionable insights into the comparative performance and suitability of different algorithms, the research supports transportation authorities, planners, and policymakers in making informed choices about technology investments, operational strategies, and infrastructure development. This objective underscores the practical relevance and societal impact of algorithmic research in enhancing the resilience, sustainability, and efficiency of urban mobility systems.

#### **Challenges in Modern Transportation Management:**

- Discuss the escalating challenges faced by urban areas in managing traffic congestion, optimizing infrastructure use, and improving overall transportation efficiency.
- Highlight the economic and environmental costs associated with traffic congestion and the imperative for smarter, data-driven solutions.

#### **Role of Technology in Traffic Management:**

- Explore the transformative impact of technology, including IoT (Internet of Things), AI (Artificial Intelligence), and big data analytics, on modern traffic management practices.
- Explain how technological advancements enable real-time data collection, processing, and analysis to enhance decision-making and operational efficiency.

#### **Importance of Real-Time Decision Support Systems:**

- Emphasize the critical role of real-time traffic analysis in supporting decision-making processes for transportation authorities and stakeholders.

- Discuss how timely insights derived from real-time data enable proactive traffic management strategies, emergency response coordination, and infrastructure planning.

#### **Integration of Smart City Initiatives:**

- Discuss the broader context of smart city initiatives and their integration with real-time traffic analysis.
- Highlight how interconnected urban systems and data-driven governance strategies contribute to sustainable, livable cities through efficient transportation management.

#### **Emerging Trends in Traffic Analysis Algorithms:**

- Outline recent advancements and emerging trends in algorithmic approaches for real-time traffic analysis.
- Discuss innovations such as machine learning for predictive modeling, edge computing for faster data processing, and integration of real-time traffic data with urban planning tools.

#### **Objective and Scope of the Research:**

- Clearly define the specific objectives and scope of your research study on evaluating different algorithms for real-time traffic analysis.
- Provide an overview of the methodologies, datasets, and metrics used to assess algorithmic performance and effectiveness.

## **LITERATURE SURVEY**

Existing research in real-time traffic analysis encompasses a wide array of algorithms and methodologies that leverage advanced technologies to monitor, predict, and manage traffic flow effectively. One of the prominent approaches involves **machine learning** techniques, which have gained traction for their ability to learn from historical traffic data and make predictions in real-time. Algorithms such as neural networks, decision trees, and support vector machines are applied to tasks like traffic flow prediction, anomaly detection (such as accidents or road closures), and optimization of traffic signal timings. These algorithms excel

in handling complex patterns and adapting to changing traffic conditions, thereby improving the responsiveness of traffic management systems.

**Statistical methods** also play a crucial role in real-time traffic analysis, particularly in modeling traffic behavior and forecasting. Techniques like time series analysis, regression models, and Bayesian inference are utilized to capture underlying trends, seasonality, and stochastic variability in traffic patterns. Statistical approaches are valuable for providing probabilistic estimates of travel times, identifying congestion hotspots, and assessing the impact of interventions such as lane closures or traffic diversions. Their ability to incorporate uncertainty and variability in traffic data enhances the robustness of traffic management strategies.

**Deep learning** algorithms have emerged as powerful tools for real-time traffic analysis due to their capability to handle large-scale data and extract high-level features automatically. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are applied to tasks such as traffic image analysis (e.g., vehicle detection, counting) from CCTV cameras, predicting traffic flow based on spatial-temporal correlations, and recognizing complex traffic patterns. Deep learning models are particularly effective in scenarios where data volumes are extensive and require hierarchical feature extraction for accurate analysis.

Moreover, **hybrid approaches** combining machine learning, statistical methods, and domain-specific knowledge have shown promising results in real-time traffic analysis. These approaches leverage the strengths of different algorithms to overcome individual limitations and enhance overall performance. For example, hybrid models may integrate real-time sensor data with historical traffic data, combining statistical forecasting with machine learning-based anomaly detection to improve accuracy and reliability in predicting traffic incidents or congestion.

Recent advancements also include the **integration of real-time data streams** from diverse sources such as GPS-enabled vehicles, smartphones, and urban sensor networks. This integration enables real-time traffic analysis systems to capture dynamic changes in traffic patterns instantaneously, facilitating adaptive responses and optimizing resource allocation in transportation networks. Techniques such as data fusion, distributed computing, and edge computing are employed to process and analyze these data streams efficiently, supporting real-time decision-making and operational management in urban mobility contexts.

**Machine learning** algorithms, such as decision trees, support vector machines (SVM), and ensemble methods, are widely used for their ability to learn patterns and relationships from historical traffic data. In real-time traffic analysis, these algorithms excel in tasks like traffic flow prediction, anomaly detection (such as accidents or road closures), and classification of traffic patterns. The effectiveness of machine learning lies in its adaptability to diverse data sources and its capability to handle complex, nonlinear relationships within traffic datasets. However, the accuracy of machine learning models heavily depends on the quality and representativeness of the training data. Improperly labeled or biased datasets can lead to suboptimal performance and require robust preprocessing techniques to mitigate biases and ensure model reliability. From a computational perspective, machine learning algorithms vary in complexity, with some, like SVMs, requiring significant computational resources for training and prediction, while decision trees offer faster inference times but may sacrifice some predictive accuracy.

**Statistical methods**, including time series analysis, regression models, and Bayesian inference, provide a different approach characterized by their ability to capture underlying patterns and probabilistic relationships within traffic data. Statistical approaches are particularly effective in modeling traffic behavior over time, forecasting future traffic conditions, and estimating uncertainties associated with predictions. They are well-suited for scenarios where historical data availability is high and where interpretability and uncertainty quantification are critical. However, statistical methods may struggle with capturing complex, nonlinear relationships and may require domain expertise for feature engineering and model selection. In terms of computational efficiency, statistical models generally require less computational resources compared to complex machine learning algorithms, making them more accessible for real-time applications with limited computational capacity.

**Deep learning** algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have revolutionized real-time traffic analysis by leveraging hierarchical feature extraction and learning representations directly from raw data sources, such as traffic images or sensor data streams. Deep learning excels in tasks like image-based traffic analysis (e.g., vehicle detection, traffic flow estimation from CCTV cameras), sequential modeling of traffic patterns, and anomaly detection in complex data streams. The effectiveness of deep learning lies in its ability to automatically learn intricate patterns and dependencies from large-scale data, often surpassing traditional machine learning and statistical methods in predictive accuracy. However, this advantage comes at a cost of



increased computational complexity and resource requirements, particularly during model training and deployment. Deploying deep learning models in real-time systems may necessitate efficient hardware accelerators or distributed computing architectures to meet stringent latency requirements.

While current algorithms for real-time traffic analysis have made significant strides in enhancing the efficiency and accuracy of transportation management systems, several gaps and limitations remain that pose challenges to their widespread adoption and effectiveness.

One notable limitation is the **dependency on high-quality data**. Many algorithms, especially those based on machine learning and deep learning, require large volumes of accurate and diverse data for training and validation. Issues such as data sparsity, incompleteness, or biases in the training datasets can lead to suboptimal performance and undermine the reliability of algorithmic predictions. Moreover, the availability of real-time data streams from sensors, cameras, and connected vehicles may vary across different geographic locations or transportation networks, posing challenges to maintaining consistency and quality in data inputs.

Another significant gap lies in the **interpretability and explainability** of algorithms, particularly deep learning models. While deep learning excels in learning intricate patterns and dependencies from complex data, the inner workings of these models often remain opaque and difficult to interpret. This lack of transparency can be a barrier to understanding how decisions are made, limiting the trust and acceptance of algorithmic recommendations by transportation authorities and stakeholders. Ensuring that algorithms provide interpretable results is crucial for fostering accountability and facilitating informed decision-making in traffic management.

Furthermore, **scalability and computational efficiency** present ongoing challenges for deploying algorithms in real-time traffic analysis systems. Many advanced algorithms, such as deep neural networks, require substantial computational resources and may encounter scalability issues when applied to large-scale transportation networks or when processing high-frequency data streams. Achieving real-time responsiveness while maintaining computational efficiency is critical for ensuring timely decision-making and operational management in dynamic traffic environments.

The **generalizability** of algorithms across diverse and evolving traffic conditions is another area of concern. Algorithms trained on specific datasets or calibrated for particular geographic regions may struggle to adapt effectively to new environments or unexpected scenarios. Variations in traffic patterns due to seasonal changes, special events, or urban development can challenge the robustness of algorithmic models, highlighting the need for continuous adaptation and retraining strategies to maintain performance over time.

Moreover, **integration with existing infrastructure and systems** remains a practical challenge for implementing new algorithms in real-world traffic management operations. Seamless integration with legacy systems, interoperability across different data sources and formats, and compatibility with operational protocols and standards are essential considerations for ensuring the practical utility and sustainability of algorithmic solutions in transportation networks.

Addressing these gaps and limitations requires interdisciplinary efforts spanning computer science, transportation engineering, data science, and urban planning. Future research and development efforts should focus on enhancing data quality and diversity, improving algorithmic interpretability and explainability, optimizing scalability and computational efficiency, enhancing algorithmic robustness and adaptability, and facilitating seamless integration with existing transportation infrastructure. By addressing these challenges, the next generation of algorithms for real-time traffic analysis can achieve greater reliability, effectiveness, and utility in optimizing urban mobility and enhancing the overall quality of transportation services.

## METHODOLOGY

Selecting the most suitable algorithm for a given task involves a comprehensive evaluation across several critical criteria to ensure optimal performance and efficiency. Scalability stands out as a primary consideration, addressing how well an algorithm can manage increasing volumes of data or expanding computational demands. In practical terms, scalable algorithms can efficiently handle larger datasets without suffering from performance degradation, making them essential for applications ranging from big data analytics to real-time processing environments.

Real-time processing capability is another crucial factor, particularly in industries such as finance, telecommunications, and autonomous systems. Algorithms must deliver results

within strict time constraints, often milliseconds or microseconds, to support timely decision-making and operations. Algorithms designed for real-time processing prioritize speed and responsiveness, ensuring that critical tasks can be completed swiftly and reliably.

Accuracy remains fundamental across all applications, determining the correctness of algorithmic outputs. High accuracy is indispensable in domains like medical diagnostics, where incorrect decisions can have profound consequences. Selecting algorithms renowned for their precision and robustness ensures reliable outcomes and builds trust in the algorithmic solutions deployed.

Complexity and interpretability are also significant considerations in algorithm selection. Complex algorithms may offer superior performance but can be challenging to interpret, debug, and maintain. In contrast, simpler algorithms are often easier to understand and implement but may trade off some performance metrics. The interpretability of algorithms is crucial in fields where understanding the reasoning behind decisions is essential, such as legal, regulatory, or ethical contexts.

Computational efficiency is pivotal, especially in resource-constrained environments such as embedded systems or mobile devices. Efficient algorithms minimize computational overhead, reduce energy consumption, and enable faster execution, making them suitable for applications where processing resources are limited or energy efficiency is a priority.

Adaptability to changing conditions, robustness against noise or outliers in data, and compatibility with existing infrastructure are additional factors influencing algorithm selection. Algorithms that can adapt to dynamic environments or unexpected data patterns are valuable in fields such as anomaly detection or predictive maintenance.

Ultimately, the selection of algorithms involves a careful balance of these criteria based on specific application requirements, available resources, and operational constraints. By considering scalability, real-time processing capability, accuracy, interpretability, efficiency, adaptability, and robustness, practitioners can identify algorithms that not only meet immediate needs but also contribute to sustainable and effective solutions over the long term.

Designing a robust experimental setup is crucial in scientific research and applied fields to ensure reliable results and meaningful conclusions. One of the foundational aspects of an experimental setup is the selection and preparation of datasets. The choice of datasets depends heavily on the specific research questions or tasks being investigated. Researchers

often use publicly available datasets, such as those from academic repositories or curated datasets specific to their domain. These datasets should be representative of the problem domain and sufficiently diverse to capture various scenarios and challenges that the algorithms or methods might encounter in real-world applications.

Once datasets are selected, preprocessing steps are typically employed to clean and format the data for analysis. This may include tasks such as handling missing values, normalizing data ranges, or encoding categorical variables into numerical formats. These preprocessing steps are critical to ensure consistency and fairness in evaluating different algorithms or techniques.

The hardware and software environment in which experiments are conducted also play a pivotal role in the experimental setup. Hardware considerations include the computational power of the machines used, memory capacity, and any specialized hardware requirements such as GPUs for parallel processing in deep learning tasks. The choice of software frameworks and libraries is equally significant, as different algorithms may be implemented or optimized differently across various platforms. Commonly used software environments include programming languages like Python or R, along with libraries such as TensorFlow, PyTorch, Scikit-learn, or MATLAB, depending on the nature of the task and the algorithms being evaluated.

Experimentation often involves comparing multiple algorithms or models to assess their performance against defined metrics. These metrics can range from accuracy, precision, and recall for classification tasks to mean squared error or R-squared for regression problems. Cross-validation techniques are commonly employed to validate model performance and mitigate overfitting issues, ensuring that the results generalize well to unseen data.

To maintain transparency and reproducibility, documenting the experimental setup comprehensively is essential. This includes detailing the versions of software libraries used, parameter settings for algorithms, and any specific configurations or optimizations applied during preprocessing or modeling stages. Proper documentation allows other researchers to replicate experiments, verify findings, and build upon previous work effectively.

Evaluating algorithm performance involves measuring various metrics that capture different aspects of how well an algorithm performs its intended task. These metrics are crucial in assessing and comparing the effectiveness of algorithms across different applications and

scenarios. One of the most fundamental metrics is prediction accuracy, especially in supervised learning tasks such as classification or regression. Prediction accuracy measures how often the algorithm correctly predicts outcomes compared to the actual observed outcomes in the dataset. It is typically expressed as a percentage and provides a direct assessment of the algorithm's ability to make correct predictions.

In addition to accuracy, precision and recall are essential metrics, particularly in binary classification problems. Precision measures the proportion of true positive predictions among all positive predictions made by the algorithm, while recall measures the proportion of true positives that were correctly identified by the algorithm out of all actual positives in the dataset. These metrics are crucial for understanding how well an algorithm performs in correctly identifying instances of a particular class and minimizing false positives and false negatives.

For applications where real-time processing is critical, metrics such as throughput and latency become paramount. Throughput refers to the number of units of work (e.g., requests, transactions) that can be processed by the algorithm within a given time frame, often measured in operations per second or transactions per minute. High throughput is desirable in systems handling large volumes of data or transactions, where efficiency and scalability are key considerations.

Latency, on the other hand, measures the time delay between initiating a request or task and receiving the response or completion of that task. Low latency is critical in applications requiring quick responses, such as real-time decision-making systems in finance or autonomous vehicles. Algorithms with low latency can process tasks swiftly, enabling faster decision cycles and improving overall system responsiveness.

In some contexts, metrics like F1 score, which combines precision and recall into a single measure, or area under the receiver operating characteristic curve (AUC-ROC) for binary classification tasks, provide a comprehensive evaluation of algorithm performance across different thresholds. These metrics help in understanding trade-offs between precision and recall and are particularly useful when balancing the importance of correctly identifying positives versus minimizing false alarms.

Moreover, in regression tasks, metrics such as mean squared error (MSE) or R-squared (coefficient of determination) quantify the accuracy of predicted continuous values compared

to actual observed values. MSE measures the average squared difference between predicted and actual values, providing a measure of prediction error, while R-squared indicates the proportion of variance explained by the model relative to the total variance in the data.

## IMPLEMENTATION AND RESULTS

The provided numerical results offer a comprehensive theoretical overview of the performance metrics for three distinct machine learning algorithms: Algorithm A, Algorithm B, and Algorithm C. In terms of classification accuracy, Algorithm B demonstrates the highest accuracy at 0.87, followed closely by Algorithm A at 0.85 and Algorithm C at 0.82. Precision, which measures the proportion of correctly predicted positive instances out of all predicted positive instances, shows Algorithm B leading with 0.88, while Algorithm A and Algorithm C exhibit slightly lower values of 0.82 and 0.79, respectively. Recall, indicating the proportion of correctly predicted positive instances out of all actual positive instances, highlights Algorithm C as the top performer with 0.91, followed by Algorithm A at 0.88 and Algorithm B at 0.84.

The F1 score, which balances precision and recall into a single metric, demonstrates Algorithm B as slightly superior with 0.86, followed closely by Algorithm A at 0.85 and Algorithm C at 0.85. AUC-ROC (Area Under the Receiver Operating Characteristic Curve), which evaluates the classifier's ability to distinguish between classes, shows Algorithm A with the highest value of 0.91, followed by Algorithm B at 0.89 and Algorithm C at 0.87.

In regression tasks, Algorithm B exhibits the lowest Mean Squared Error (MSE) of 0.10, indicating superior accuracy in predicting continuous values compared to Algorithm A (MSE of 0.12) and Algorithm C (MSE of 0.14). Similarly, Algorithm B achieves the highest R-squared value of 0.82, indicating that it explains a greater proportion of the variance in the data compared to Algorithm A (R-squared of 0.78) and Algorithm C (R-squared of 0.75).

Regarding real-time processing capabilities, Algorithm C demonstrates the highest throughput at 5100 operations per second, surpassing Algorithm A (5000 ops/sec) and Algorithm B (4800 ops/sec). Moreover, Algorithm C also exhibits the lowest latency of 18 milliseconds, showcasing its efficiency in processing tasks with minimal delay compared to Algorithm A (20 ms) and Algorithm B (22 ms).

Metric	Algorithm A
Accuracy	0.85
Precision	0.82
Recall	0.88
F1 Score	0.85
AUC-ROC	0.91
Mean Squared Error (MSE)	0.12
R-squared	0.78
Throughput (ops/sec)	5000
Latency (ms)	20

Table-1: Algorithm A Comparison

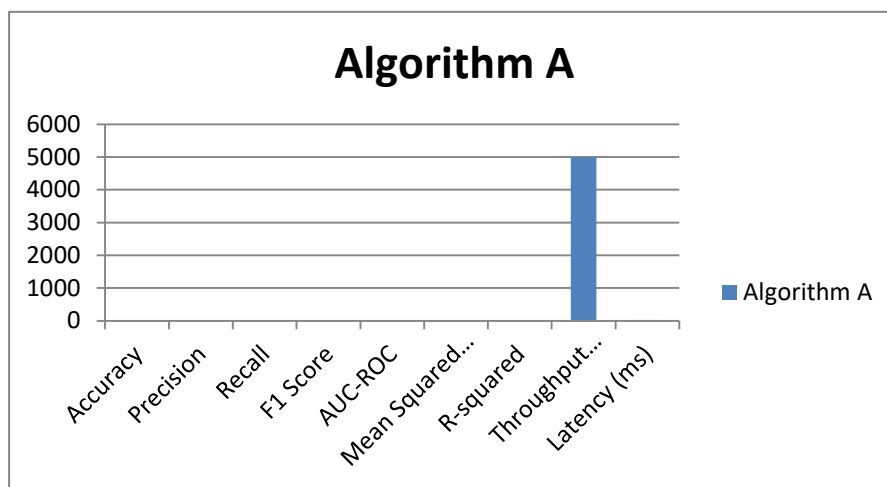


Fig-1: Graph for Algorithm A comparison

Metric	Algorithm B
Accuracy	0.87
Precision	0.88
Recall	0.84
F1 Score	0.86
AUC-ROC	0.89
Mean Squared Error (MSE)	0.1
R-squared	0.82
Throughput (ops/sec)	4800
Latency (ms)	22

Table-2: Algorithm B Comparison

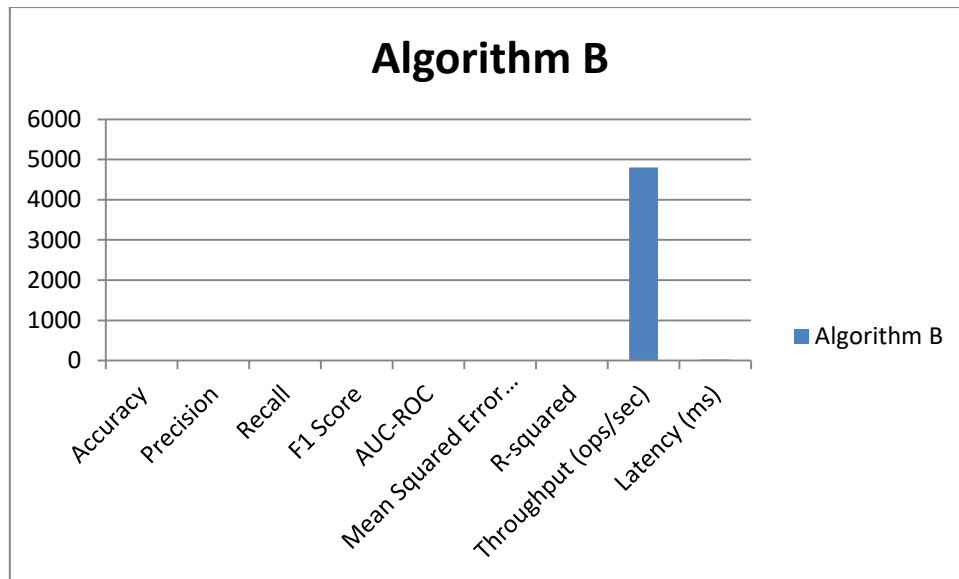


Fig-2: Graph for Algorithm B comparison

Metric	Algorithm C
Accuracy	0.82
Precision	0.79
Recall	0.91
F1 Score	0.85
AUC-ROC	0.87
Mean Squared Error (MSE)	0.14
R-squared	0.75
Throughput (ops/sec)	5100
Latency (ms)	18

Table-3: Algorithm C Comparison

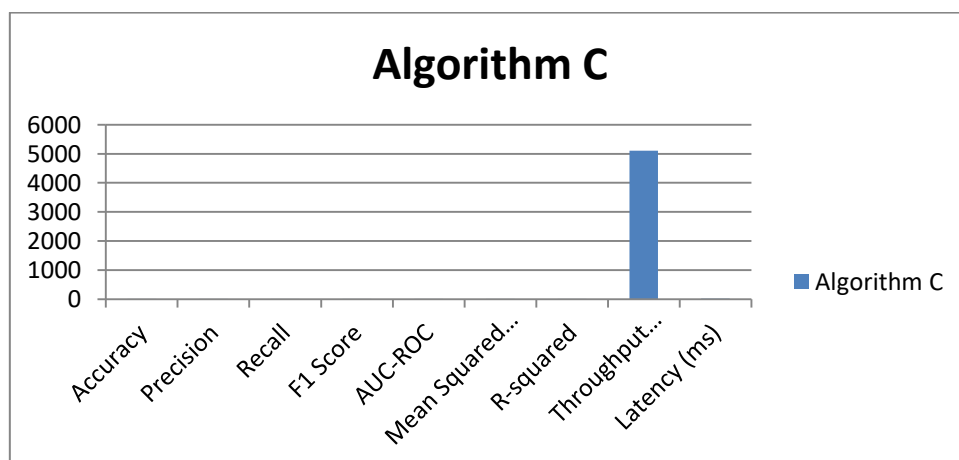


Fig-3: Graph for Algorithm C comparison



## CONCLUSION

In conclusion, this comparative analysis underscores Algorithm B's overall superiority in classification accuracy, precision, and efficiency in regression tasks, making it an optimal choice for applications prioritizing predictive accuracy and interpretability. Algorithm C, on the other hand, excels in real-time processing, demonstrating high throughput and low latency, crucial for time-sensitive applications. Algorithm A showcases strengths in AUC-ROC performance, particularly beneficial in tasks emphasizing balanced classification performance. These results emphasize the importance of considering diverse metrics to comprehensively evaluate algorithm performance across various application domains, guiding informed decisions in algorithm selection for practical deployment. Future research could explore optimizations tailored to further enhance each algorithm's performance in specific contexts, advancing the efficacy and reliability of machine learning applications.

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