

**DETEKSI PENCILAN PADA *DATA STREAM* POLUSI CAHAYA LANGIT  
MALAM DENGAN ALGORITMA EXACT-STORM**

**SKRIPSI**

diajukan untuk memenuhi  
salah satu syarat untuk memperoleh  
gelar Sarjana Komputer



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ALAM  
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2024**

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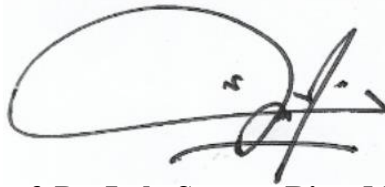
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# Deteksi Pencilan pada *Data Stream* Polusi Cahaya Langit Malam dengan Algoritma exact-STORM

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## ABSTRAK

Polusi cahaya telah menjadi isu global yang menghalangi pengamatan astronomi dan mengganggu ekosistem. Data hasil sensor *Sky Quality Meter* (SQM) diambil secara sekuens sehingga menghasilkan data deret waktu yang sangat memungkinkan adanya pencilan saat pengamatan, sehingga deteksi pencilan dalam data SQM penting dilakukan untuk mengetahui apakah pencilan yang terdeteksi disebabkan oleh fenomena fisis atau gangguan dalam pengukuran. Penelitian berfokus pada pengembangan program deteksi pencilan berbasis *real-time streaming* menggunakan algoritma exact-STORM dengan *platform big data streaming* Apache Kafka. Untuk mencapai tujuan tersebut, metode yang digunakan dalam penelitian ini terdiri dari: (1) *data collection*, (2) perhitungan radius dengan metode Chebyshev, (3) *set up* Apache Kafka, dan (4) deteksi pencilan dengan algoritma exact-STORM. *Dataset* yang digunakan berasal dari Repositori Ilmiah Nasional (RIN) Dataverse yang dikumpulkan oleh Badan Riset dan Inovasi Nasional (BRIN) yang menyediakan data hasil sensor SQM dengan resolusi 1 menit yang dicatat secara kontinu setiap malam. Penelitian ini dapat membantu para ahli di bidang astrofisika untuk membuat program deteksi pencilan yang berbasis *real-time* secara *streaming*. Program ini secara efektif mendeteksi pencilan secara *real-time streaming* untuk data selama tujuh bulan dengan skor proporsi sebesar 51,11%, *error rate* sebesar 1,61%, dan akurasi sebesar 98,39%. Penelitian ini memvalidasi bahwa metode deteksi pencilan berbasis jarak dapat digunakan untuk mendeteksi pencilan secara *real-time* pada data kecerahan langit malam.

**Kata Kunci:** Apache Kafka, Astrofisika, *Data Stream*, exact-STORM, Polusi Cahaya, Deteksi Pencilan, *Streaming*

# Outlier Detection in Night Sky Light Pollution Data Streams using the exact-STORM Algorithm

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## ABSTRACT

Light pollution has emerged as a global issue, obstructing astronomical observations and disrupting ecosystems. Data from the Sky Quality Meter (SQM) sensor results sequentially collected in time series data, making it a data stream and highly likely to have outliers. Therefore, outlier detection in SQM data is crucial to determine whether the detected anomalies are due to physical phenomena or measurement disturbances. This study focuses on developing a real-time streaming outlier detection program using the exact-STORM algorithm integrated with the Apache Kafka big data streaming platform. To achieve this objective, the research methodology comprises: (1) data collection, (2) radius calculation using the Chebyshev method, (3) Apache Kafka setup, and (4) outlier detection using the exact-STORM algorithm. The dataset used originates from the National Scientific Repository (RIN) Dataverse, collected by the National Research and Innovation Agency (BRIN), providing SQM sensor data recorded continuously every night with a resolution of 1 minute recorded continuously every night. This research can assist astrophysics experts in developing a real-time streaming outlier detection system. The program effectively detects outliers in real-time streaming for data over seven months, achieving a proportion score of 51.11%, an error rate of 1.61%, and an accuracy of 98.39%. This study validates that distance-based outlier detection methods can be effectively employed to identify outliers in real-time night sky brightness data.

**Keywords:** *Apache Kafka, Astrophysics, Data Stream, exact-STORM, Light Pollution, Outlier Detection, Streaming*

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