DETEKSI AKSI KEKERASAN PADA VIDEO MENGGUNAKAN ARSITEKTUR *DUAL-STREAM* CONVLSTM DENGAN OPTIMASI *FRAME GROUPING*

SKRIPSI

Diajukan Untuk Memenuhi Sebagian dari Syarat Memperoleh Gelar Sarjana Komputer Program Studi Ilmu Komputer

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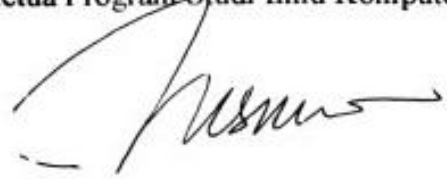

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ABSTRAK

Sistem pengawasan konvensional sering kali bersifat reaktif dan tidak efisien dalam menangani insiden kekerasan, sehingga dibutuhkan solusi proaktif yang dapat memberikan peringatan secara dini. Penelitian ini bertujuan untuk merancang, membangun, dan menguji sebuah sistem deteksi kekerasan *real-time* yang tangguh dan efisien secara komputasi. Metode yang diusulkan menggunakan arsitektur *dual-stream* ConvLSTM yang secara paralel memproses fitur deteksi perubahan dan kerangka manusia. Efisiensi komputasi ditingkatkan melalui teknik *frame grouping* dan sebuah modul filter yang hanya menganalisis video saat terdeteksi adanya gerakan signifikan. Hasil eksperimen menunjukkan performa model dengan f1-*score* sebesar 78.62% dan penghematan waktu eksekusi GPU hingga 90.8% berkat penggunaan filter pada video dengan kamera statis dan aktivitas rendah. Sistem *end-to-end* yang diuji terbukti layak untuk penerapan *real-time*, dengan latensi pemrosesan maksimum 0.9891 detik. Penelitian ini berhasil mengembangkan sebuah kerangka kerja sistem deteksi kekerasan yang menyeimbangkan antara akurasi, ketangguhan, dan efisiensi komputasi, sehingga praktis untuk penerapan di dunia nyata.

Kata kunci: ConvLSTM, Deteksi Kekerasan, Deteksi Perubahan, *Frame Grouping*, Kerangka Manusia

VIOLENCE DETECTION IN VIDEO USING DUAL-STREAM CONVLSTM ARCHITECTURE WITH FRAME GROUPING OPTIMIZATION

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ABSTRACT

Conventional surveillance systems are often reactive and inefficient in handling violent incidents, necessitating proactive solutions capable of providing early warnings. This research aims to design, build, and test a robust and computationally efficient real-time violence detection system. The proposed method adopts a dual-stream ConvLSTM architecture that processes change detection and human skeleton features in parallel. Computational efficiency is enhanced through the frame grouping technique and a filter module that only analyzes video when significant motion is detected. Experimental results show a model performance with an f1-score of 78.62% and GPU execution time savings of up to 90.8% on videos with static cameras and low activity. The tested end-to-end system is proven viable for real-time application, with a maximum processing latency of 0.9891 seconds. This research successfully develops a framework for a violence detection system that balances accuracy, robustness, and computational efficiency, making it practical for real-world implementation.

Keywords: *Change Detection, ConvLSTM, Frame Grouping, Human Skeleton, Violence Detection*

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