ABSTRAK

Perkembangan industri *video game* yang pesat membawa dampak signifikan terhadap pola perilaku remaja, khususnya terkait dengan paparan konten kekerasan dalam permainan *digital*. Konten seperti adegan kekerasan, penggunaan senjata, dan darah sering kali tersembunyi di balik *gameplay* yang menarik, tanpa disertai sistem *rating* yang memadai. Kondisi ini menimbulkan kekhawatiran akan potensi peningkatan perilaku agresif di kalangan pemain muda, serta menunjukkan lemahnya sistem pengawasan konten *digital* yang ada. Diperlukan solusi teknologi yang mampu secara otomatis mendeteksi elemen kekerasan seperti darah dalam video game guna meningkatkan keamanan dan pengawasan terhadap konten hiburan *digital*. Maka dari itu, penelitian ini akan menerapkan metode YOLOv8 serta mengevaluasi tingkat akurasinya menggunakan beberapa kombinasi *hyperparameter* dalam mendeteksi objek darah dalam *video game*.

Tahapan penelitian mencakup pengumpulan data secara primer sejumlah 988 citra hasil tangkapan layar dari *gameplay*, yang kemudian diklasifikasikan ke dalam dua kelas utama, yaitu *blood* dan *background*. Lalu dilakukan tahap *preprocessing* data dengan melakukan *cleaning*, anotasi, *splitting*, *resize*, dan agumentasi. Augmentasi pada data latih dilakukan dengan teknik transformasi visual seperti rotasi, *flip*, serta pengaturan saturasi dan pencahayaan. Data yang sudah melalui tahap *preprocessing* kemudian digunakan dalam pelatihan model. Model YOLOv8n dilatih menggunakan 7 kombinasi konfigurasi *hyperparameter*, dan performanya diuji berdasarkan metrik evaluasi seperti *precision*, *recall*, dan nilai *mean average precision* (mAP) untuk mencari kombinasi *hyperparameter* terbaik.

Hasil dari pengujian 7 kombinasi *hyperparameter* ditemukan kombinasi *hyperparameter* terbaik, yaitu dengan nilai *hyperparameter lr0* (*learning rate* awal) 0.001 dan *weight decay* 0.0001, mendapatkan metrik evaluasi tertinggi dengan nilai *precision*, *recall*, dan mAP50 masing-masing sebesar 89,6%, 81%, dan 89,1%. Namun, pengujian aktual menggunakan model terbaik menujukkan hasil yang berbeda. Dengan menggunakan dua sistem yang dibangun, didapatkan *average precison* pada sistem deteksi video sebesar 76,3% dan pada sistem deteksi rekam layar sebesar 69,3%. Penurunan akurasi pada pengujian aktual disebabkan oleh kemunculan *false positive*, yaitu ketika model mendeteksi objek abstrak seperti pohon, jejak sepatu di karpet, atau elemen visual lain yang menyerupai darah. Selain itu, keterbatasan performa perangkat turut memengaruhi efektivitas sistem dalam melakukan deteksi secara *real-time*.

Kata Kunci: Deteksi Objek, Deteksi Kekeraasan, *Video Game*, YOLOv8, Deteksi Darah

ABSTRACT

The rapid development of the video game industry has significantly influenced adolescent behavior patterns, particularly concerning exposure to violent content in digital games. Elements such as violent scenes, weapon use, and depictions of blood are often embedded within engaging gameplay, frequently without adequate rating systems. This raises concerns about the potential increase in aggressive behavior among young players and highlights the weakness of existing digital content monitoring systems. A technological solution capable of automatically detecting violent elements—such as the presence of blood—in video games is needed to enhance content safety and supervision. Therefore, this study aims to implement the YOLOv8 method and evaluate its accuracy using various combinations of hyperparameter in detecting blood-related violent content in video games.

The research stages include the collection of 988 primary image datasets captured from gameplay screenshots, which are then classified into two main categories: blood and background. The preprocessing stage involves data cleaning, annotation, splitting, resizing, and augmentation. Augmentation of the training data is performed using visual transformation techniques such as rotation, flipping, and adjustment of saturation and brightness. The preprocessed data was used to train a YOLOv8n model using seven different hyperparameter configurations, and its performance is evaluated based on metrics such as precision, recall, and mean average precision (mAP) to determine the optimal configuration.

The evaluation of the seven hyperparameter combinations identified the best configuration with learning rate (lr0) of 0.001 and weight decay of 0.0001, achieving the highest evaluation metrics with a precision of 89.6%, recall of 81%, and mAP50 of 89.1%. However, real-world testing using the best-performing model yielded different results. Two implemented systems showed average precision values of 76.3% for video detection and 69.3% for screen recording detection. The decline in accuracy during real-world testing was attributed to false positives, where abstract objects such as trees, carpet patterns, or other visually similar elements were misidentified as blood. Additionally, hardware limitations also affected the system's performance in conducting real-time detection.

Keywords: *Object Detection, Violence Detection, Video Game, YOLOv8, Blood Detection*