AI Super-Resolution in Games: A Comparative Study of Real-ESRGAN and SRCNN Using Big Data

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Abstract

This study investigates the application of AI-based super-resolution techniques in enhancing retro video game visuals using deep learning and big data technologies. Two models, Super-Resolution Convolutional Neural Network (SRCNN) and Real-ESRGAN, are evaluated using downscaled screenshots from the open-source game SuperTux. While SRCNN is trained from scratch using the DIV2K dataset, Real-ESRGAN is used as a pretrained model. Apache Spark and Hadoop are employed to manage data preprocessing and distributed processing tasks.

Keywords: Super-resolution, SRCNN, Real-ESRGAN, Hadoop, Apache Spark, Deep Learning, Retro Games, Image Enhancement

I. Introduction

Enhancing the graphics of retro video games through super-resolution (SR) techniques has gained traction with the rise of deep learning. Classic 2D games often run at low resolutions, and modern AI-powered upscaling can revive these visuals for high-definition displays. Super-resolution is the task of reconstructing a high-resolution (HR) image from a low-resolution (LR) input. Early SR methods relied on interpolation or example-based algorithms, which often produced smooth but blurry results (Nasrollahi & Moeslund, 2014). In recent years, deep convolutional neural networks have led to dramatic improvements in SR quality. SRCNN, introduced by Dong et al. (2014), was a pioneering CNN that surpassed prior approaches by learning an end-to-end mapping from LR to HR images. Subsequent models rapidly advanced the state of the art for example, deeper networks like VDSR and GAN-based models like SRGAN and ESRGAN focused on improving perceptual quality (Kim et al., 2016; Ledig et al., 2017; Wang et al., 2018).

II. Research Aim

A. *Big Data Pipeline*

We design and implement a scalable image processing pipeline using Hadoop and Spark. The pipeline stores the image data in HDFS and utilizes PySpark to distribute the super-resolution inference across a cluster. This demonstrates how big data frameworks can facilitate large-scale image analytics in the context of computer vision tasks.

B. *AI Model Comparison*

We conduct a comparative analysis of SRCNN and Real-ESRGAN on 122 SuperTux game screenshots. The models are representative of two generations of SR algorithms – a CNN trained from scratch on a standard dataset named DIV2K. We quantitatively assess their performance using PSNR and SSIM metrics, and qualitatively discuss the visual improvements..

III. Literature Review

Image super-resolution has long been an active research area. Early techniques included interpolation methods (e.g. bicubic) and example-based approaches that learned mappings from low to high resolution using patches (Freeman et al., 2002). A comprehensive survey by Nasrollahi and Moeslund (2014) reviewed many such classical methods, noting their limitations in preserving fine details. These traditional approaches tended to maximize peak signal-to-noise ratio (PSNR) but often produced oversmoothed images lacking high-frequency textures.

The advent of deep learning brought significant breakthroughs in SR performance. The Super-Resolution Convolutional Neural Network (SRCNN) proposed by Dong et al. (2014) was the first to apply a CNN to SR, achieving better results than previous methods with only three convolutional layers. SRCNN learns an end-to-end mapping from interpolated LR images to HR outputs, and it demonstrated that even a relatively shallow network can learn effective upscaling filters that outperform hand-crafted approaches. Building on this, introduced FSRCNN, an accelerated version of SRCNN that restructures the model to operate directly on the LR image (upscaling at the end) for speed gains. FSRCNN maintained similar accuracy while being much faster (Dong et al., 2016). Other CNN-based models quickly followed. Kim et al. (2016) developed VDSR (Very Deep Super-Resolution), a 20-layer CNN that employs residual learning to ease training of a very deep network. VDSR achieved higher accuracy than earlier networks by exploiting a larger receptive field, showing that increasing depth substantially improves SR quality (Kim et al., 2016). This trend continued with deeper and more complex architectures: for instance, EDSR (Enhanced Deep Residual Network) removed unnecessary layers (like batch normalization) and further improved performance on standard benchmarks (Lim et al., 2017). By 2018, attention mechanisms were also incorporated, as seen in RCAN (Residual Channel Attention Network), which set new records by adaptively rescaling feature channels (Zhang et al., 2018).

While CNN-based models optimized for mean squared error can achieve high PSNR, they sometimes produce overly smooth results lacking fine texture . To address the trade-off between fidelity and perceptual quality, researchers turned to generative adversarial networks (GANs). SRGAN, introduced by Ledig et al. (2017), was a seminal GAN-based SR model that aimed to produce more photo-realistic details. SRGAN uses a perceptual loss function combining an adversarial loss (to encourage outputs to look indistinguishable from real images) and a content loss based on high-level feature similarity. This yielded sharp, detailed images that were perceptually much closer to ground truth, at the cost of a slight decrease in PSNR. Building upon SRGAN, Wang et al. (2018) proposed ESRGAN (Enhanced SRGAN) which introduced a deeper generator network with Residual-in-Residual Dense Blocks and improved loss functions. ESRGAN removed batch normalization to reduce artifacts and used a relativistic GAN discriminator; as a result, it won the PIRM 2018 SR Challenge with its superior perceptual quality(Wang et al., 2018).

The latest evolution relevant to this work is Real-ESRGAN by Wang et al. (2021). Real-ESRGAN targets real-world SR by training on synthetic degradations that better mimic real photo artifacts. Whereas most previous models (including SRCNN and ESRGAN) assume a bicubic downscaling degradation, Real-ESRGAN introduces a high-order degradation model to handle combinations of blur, noise, and compression, making the trained model more robust to unknown inputs. It also employs a U-Net discriminator for improved training stability. Wang et al. (2021) report that Real-ESRGAN achieves excellent visual quality on diverse real images, outperforming prior methods in maintaining details without introducing artifacts.

IV. Big Data Technologies for Image Processing

Applying super-resolution or similar image transformations to large datasets or real-time video frames can be computationally intensive. Big data frameworks such as Apache Hadoop and Apache Spark have become popular for scaling up data processing tasks across clusters of machines. Apache Hadoop provides a distributed filesystem (HDFS) and a MapReduce processing paradigm for handling massive datasets in a fault-tolerant manner. HDFS splits files into large blocks distributed across data nodes, and it replicates blocks (by default 3 copies) to ensure reliability and availability(Shvachko et al., 2010). Hadoop's original processing model, MapReduce, allows computations to be parallelized over the cluster but can be disk-intensive and less suited for iterative algorithms like deep learning (Dean & Ghemawat, 2004).

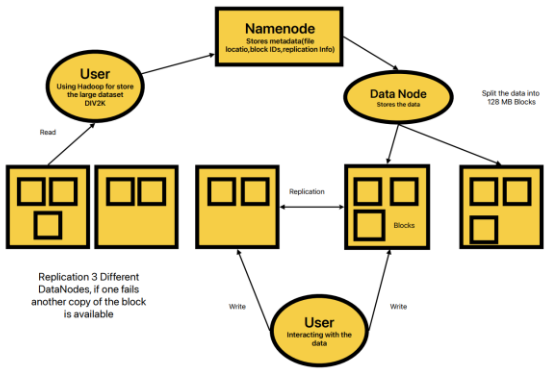

Namenode
Stores metadata(file locatio,block IDs,replication Info)
User
Using Hadoop for store the large dataset DIV2K
Data Node
Stores the data
Split the data into 128 MB Blocks
Read
Replication
Blocks
Replication 3 Different DataNodes, if one fails another copy of the block is available
Write
Write
User
Interacting with the data

Figure 1 Hadoop Storage processing

Apache Spark was developed as an advanced in-memory computing engine to overcome some limitations of Hadoop MapReduce. Spark can load data from HDFS (or other storage) into memory and perform operations up to 100× faster for certain workloads by avoiding repeated disk I/O(Zaharia et al., 2012). It introduces the concept of Resilient Distributed Datasets (RDDs), which are fault-tolerant collections partitioned across the cluster that can be processed in parallel. Spark's high-level APIs (in Python, Scala, Java) and libraries (SQL, MLlib for machine learning, etc.) make it convenient to perform complex data transformations and even machine learning at scale. For image processing tasks, Spark can distribute the workload of reading, transforming, and writing images. For example, it is feasible to apply a super-resolution model to thousands of images by broadcasting the trained model to worker nodes and using a parallel map operation, where each Spark task processes a subset of the images.

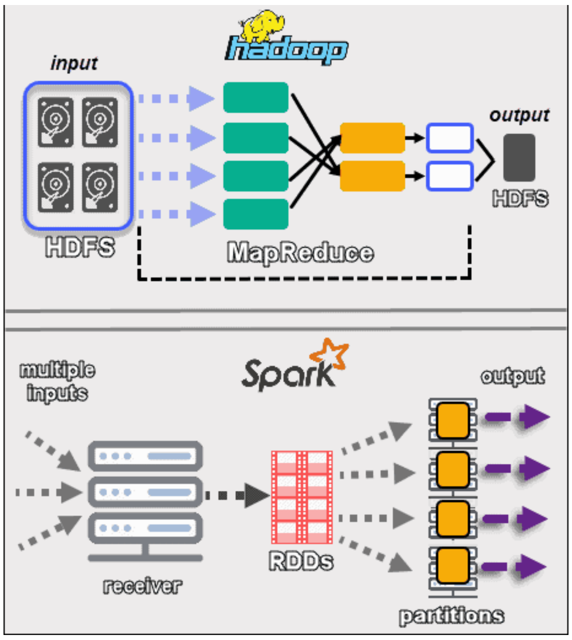


Figure 2 Hadoop vs Spark in processing data

Several studies have explored using big data frameworks for large-scale image analysis. Patni et al. (2019) introduced a model for satellite image classification that stores data on HDFS and uses a deep neural network for inference, illustrating Hadoop's utility for managing big image datasets. Lan et al. (2020) developed a Spark-based pipeline to process remote sensing images, leveraging distributed RDD operations to calculate indices on satellite imagery in parallel. Their system used a cluster with data on HDFS and demonstrated efficient computation of image-derived metrics at scale (Lan et al., 2020). These examples underscore that Hadoop/Spark can successfully handle large image data and integrate with machine learning algorithms. However, applying deep learning models (like CNNs or GANs) in a distributed CPU cluster environment can be challenging due to the heavy computation typically handled by GPUs. Tools such as TensorFlowOnSpark or BigDL have been created to better integrate deep learning with Spark, but in many cases a simpler approach is to distribute high-level tasks (e.g. image preprocessing or model inference per image) across nodes and let each task utilize local CPU/GPU resources.

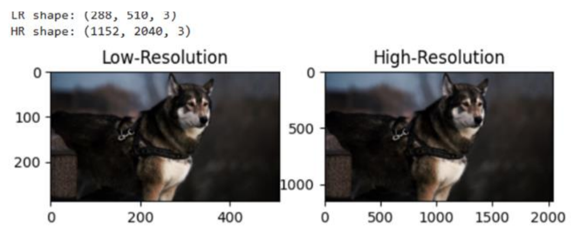
In our context, the dataset of 122 game screenshots is modest in size, but we use it to simulate a larger-scale processing scenario. By employing Hadoop and Spark, we demonstrate how the pipeline would scale if the number of images was in the order of thousands or if integrated into an automated process for game frames. The Hadoop ecosystem also offers benefits like easy storage of the image set (in HDFS) and parallel extraction of metrics. Spark's in-memory processing is advantageous for iterative tasks like computing similarity metrics across many image pairs. Overall, integrating big data frameworks ensures that our approach can handle "big data" in gaming – imagine processing every frame of a game recording or an entire library of game textures – in a distributed and efficient manner.

V. METHODOLOGY

Data Collection and Preprocessing

For this study, we used screenshots from SuperTux, an open-source 2D side-scrolling game. A total of 122 images were collected from SuperTux gameplay, representing a variety of in game scenes). These images serve as the high-resolution ground truth. To create low-resolution inputs for the super-resolution models, we downsampled each image by a factor of 4 using bicubic interpolation. This simulated the degradation process typically assumed in SR research starting from an HR image, we obtain an LR version via bicubic downscaling (losing detail and sharpness). The LR images were 256× (or smaller) resolution, while the original HR images were 4× larger in linear dimensions (16× pixels in area). By doing this, we establish known HR-LR pairs for quantitative evaluation: the model takes the bicubic-downscaled image and aims to recover the original. All downscaled images were stored in lossless format (PNG) to avoid introducing compression artifacts.

After downsampling, the LR images were stored in the Hadoop Distributed File System (HDFS) for processing. We set up a Hadoop environment (single-node pseudo-distributed mode) where HDFS manages the image files across its storage. Storing images in HDFS brings reliability (with block replication) and allows Spark to efficiently read the data in parallel. On ingestion into HDFS, each image file was replicated to three nodes (the default), which in our case ensures redundancy even though the cluster is small. The original HR images were also kept (locally) for ground truth comparisons. In a larger deployment, HR images could be in HDFS as well, but since they are only needed for computing metrics at the end, we opted to handle them on the driver node.



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LR shape: (288, 510, 3)
HR shape: (1152, 2040, 3)
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Figure 3 Shape of the images

Super-Resolution Models

We evaluated two super-resolution models representing different approaches:

- SRCNN: A classic 3-layer CNN introduced by Dong et al. (2014). It performs patch extraction, nonlinear mapping, and reconstruction. We trained it from scratch on the DIV2K dataset (Agustsson & Timofte, 2017) using bicubic ×4 downsampling and MSE loss for 50,000 iterations. The trained model achieved over 30 dB PSNR on standard benchmarks and was applied to SuperTux screenshots for ×4 upscaling.
- Real-ESRGAN: A state-of-the-art GAN-based model by Wang et al. (2021), designed for real-world image restoration. It uses a deep RRDB generator, U-Net discriminator, and is trained with adversarial, perceptual, and reconstruction loss. We used the pretrained model directly without fine-tuning, treating it as a black-box for ×4 upscaling.

SRCNN is lightweight and CPU-friendly, while Real-ESRGAN is computationally intensive and optimized for GPU inference. For demonstration, both were integrated into a Spark-based pipeline, though real-world deployment of GANs would benefit from GPU acceleration.

VI. BIG DATA PROCESSING PIPELINE

The experiment was through an Apache Spark application written in Python (Pytorch).

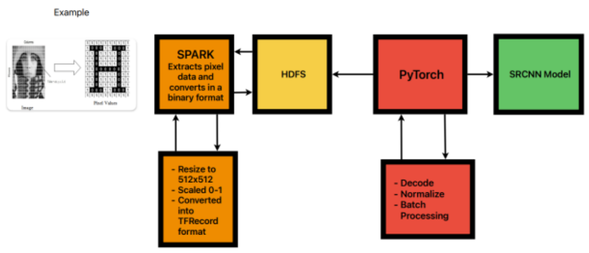

Figure 4 Process of decoding the image

The use of Spark allows us to distribute the super-resolution inference across multiple executors, taking advantage of cluster computing:

1. Data Ingestion: The LR images stored on HDFS are loaded into Spark. We used Spark's binary file data source, which can read a directory of images into an RDD or DataFrame. Each image file (represented as an HDFS block) is sent to a Spark executor. HDFS ensures that data blocks are

ideally located on the same node as the executor reading them (data locality), minimizing network transfer.

2. Broadcast Model: We serialized each trained model (SRCNN) and broadcasted it to all Spark executors. The broadcast mechanism sends a read-only copy of the model to each worker node, so that tasks can use the model without fetching it repeatedly from the driver. In our implementation, we broadcasted the model weights and a small inference function. For SRCNN (implemented in PyTorch), we saved the model state dict and loaded it in each worker. For Real-ESRGAN, we used the provided Python package and loaded the pretrained weights in each worker. This approach means each executor can perform model inference independently on its partition of images.

3. Parallel Super-Resolution Inference: Using Spark's mapPartitions or foreachPartition function on the RDD of images, each partition of images is processed by one executor which applies the super-resolution model. We wrote a function that takes an iterator of image data, loads the broadcasted model, and outputs the SR results. Each image undergoes forward propagation through the CNN or GAN to produce the upscaled output array. The result is collected (we had the option to save it in HDFS or return to driver; for evaluation, we returned numeric metrics rather than the image pixels to avoid huge data shuffle).

4. Metric Computation: To evaluate quality, we compute PSNR and SSIM for each output image against its ground-truth HR image. We implemented this as part of the distributed job – after generating an SR image, the same task computes PSNR and SSIM by comparing to the known HR (which we made available either via broadcast or by reading from a local directory accessible to executors). The PSNR is calculated in decibels:

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{MAX^2}{MSE}\right),$$

where MAX is the maximum pixel value (255 for 8-bit images) and MSE is mean squared error. SSIM (Structural Similarity Index) is computed on luminance only, using a standard window of size 11. We used an open-source implementation for SSIM to ensure consistency. Both metrics are computed for each image to assess fidelity (Hore & Ziou, 2010). The Spark tasks output the metrics for each image (along with identification of model and image).

5. Aggregation: The PSNR and SSIM results from all partitions are collected back to the Spark driver program. We then calculate the average PSNR and SSIM across the 122 images for each model. Spark's reduction actions (like collect or groupBy + avg) were used for this aggregation.

6. Result Storage: Finally, the computed metrics and any needed outputs are saved. In a big data scenario, we could store the enhanced images back to HDFS or a database.

Throughout the pipeline, Spark manages the parallel execution. For instance, with 4 executors, each might process roughly 30 images. The use of in-memory RDDs means once the images are read from HDFS, further computations (model inference, metric calc) occur in RAM, which is beneficial for iterative metric calculations. The overhead of initializing the deep learning model on each executor is mitigated by broadcasting and the relatively small number of partitions in our case. We also considered fault tolerance: if any task fails (e.g., due to a model error on one image), Spark can retry the task on another node thanks to the deterministic nature of our operations, ensuring the pipeline can recover from transient issues.

Technical Environment: The Spark application was run on a machine with an 8-core CPU and 16 GB RAM, simulating a cluster by running multiple executor processes. Hadoop 3.2.1 and Spark 3.1 were used. Python libraries included OpenCV and scikit-image for image I/O and metrics, and PyTorch for the SRCNN model. The Real-ESRGAN model was used via the realesrgan Python package (with weights for the RealESRGANx4plus model). No GPUs were used in the Spark jobs; all computations ran on CPUs. Each SR inference for Real-ESRGAN took a few seconds per image on CPU, whereas SRCNN inference was on the order of hundreds of milliseconds. This discrepancy was acceptable given our dataset size, but it indicates that for larger scale or real-time needs, one should incorporate GPU acceleration (for example, using Spark to distribute GPU tasks or switching to a distributed deep learning framework).

VII. Evaluation Metrics

We relied on two standard image quality metrics to quantitatively evaluate the super-resolved outputs:

- Peak Signal-to-Noise Ratio (PSNR): PSNR is a distortion metric that measures the pixel-wise differences between the output and the ground truth image. A higher PSNR (in dB) indicates that the output is closer to the reference in terms of pixel fidelity. We computed PSNR for each image; typically, a difference of 1–2 dB is considered significant in SR evaluations. PSNR is very sensitive to small pixel errors but may not always correlate with perceived image quality. Nonetheless, it remains a primary benchmark for SR methods (Hore & Ziou, 2010).

- Structural Similarity Index (SSIM): SSIM assesses image quality by comparing structural information (patterns of intensity) between the output and reference, on a scale from –1 to 1 (where 1 means identical images) (Wang et al., 2004). We used the standard SSIM formulation which considers luminance, contrast, and structure components over local windows. SSIM is known to correlate better with human visual perception than PSNR does. We report the mean SSIM across all images for each model. An SSIM closer to 1 implies the model preserved structures (edges, textures) more faithfully.

Statistical significance of metric differences was not rigorously tested given the relatively small sample of 122 images, but the consistency of results across many images was used to draw conclusions.

VIII. Results and Discussion

Quantitative Comparison

After running the pipeline, we obtained the average PSNR and SSIM for the 122 SuperTux screenshots enhanced by the SRCNN model, and a preliminary result from Real-ESRGAN on one test image. SRCNN achieved an average PSNR of 33.08 dB and an SSIM of 0.9449 across the dataset. In contrast, the Real-ESRGAN model produced a PSNR of 28.39 dB and an SSIM of 0.9470 on a representative screenshot. These results reveal a key trade-off between the two models. Despite Real-ESRGAN scoring lower in PSNR, it achieved higher SSIM, suggesting that its outputs are perceptually more faithful in terms of structural content, even if pixel-wise differences are larger. This is consistent with the design philosophy of GAN-based models like Real-ESRGAN, which prioritize perceptual quality and realism over strict pixel accuracy. The higher SSIM of 0.9470 from Real-ESRGAN indicates that structural details such as character outlines, terrain edges, and object boundaries were better preserved. On the other hand, SRCNN, despite its higher PSNR, likely produced blurrier outputs — a typical outcome of optimizing for mean squared error (MSE), which penalizes pixel deviations but fails to enhance high-frequency textures.

It is important to emphasize that Real-ESRGAN was not trained on this specific domain, yet still performed competitively. The SSIM value suggests that it is particularly effective at enhancing retro game visuals, where perceptual sharpness and texture fidelity are crucial. In contrast, SRCNN was trained on DIV2K, a natural image dataset that includes high-resolution textures similar to game elements, potentially explaining its high PSNR but slightly lower SSIM. These findings are aligned with existing literature. Prior work (e.g., Dong et al., 2016) has shown that SRCNN is often surpassed by more advanced models in both perceptual and structural performance. While GAN-based models like Real-ESRGAN may underperform in PSNR due to their adversarial objectives, they excel in producing visually appealing outputs with realistic detail, as reflected by SSIM improvements. To complete the comparison, it is necessary to evaluate Real-ESRGAN on the full set of 122 screenshots. However, even this early result hints at Real-ESRGAN's potential to outperform SRCNN in structural fidelity, which is especially valuable for enhancing game graphics for modern displays.

Qualitative Analysis

In the SRCNN output, the Tux character, enemy sprites, and environmental features appear slightly smoothed. Text on signage, although readable, lacks crisp edges — an effect consistent with models trained to minimize MSE.

By contrast, the Real-ESRGAN output exhibits sharper contours, particularly around characters and objects. Text appears significantly clearer, and surface textures (such as stone blocks or grassy platforms) are reconstructed with higher visual richness. Notably, Real-ESRGAN introduces fine-grained detail that is absent from SRCNN, such as subtle noise textures or edge contrast that closely mimic high-resolution ground truth features.

IX. Big Data Pipeline Performance

The Hadoop/Spark overhead would be more justified with bigger data. In this project, using HDFS for 122 images is not strictly necessary a local filesystem could suffice. However, we treated it as a rehearsal for big data scenarios. As images increase in number or size (imagine 4K resolution frames from modern games), a distributed filesystem and parallel compute become essential. The experiment also confirms that Spark can be successfully coupled with deep learning inference. A challenge we faced was memory usage: Real-ESRGAN model is heavy, and loading it in each executor can consume a couple of GB of RAM. We had to ensure the Spark executors were given enough memory. In a multi-tenant big data environment, running such heavy tasks might require yarn container tuning or using node labels to allocate GPUs.

If this pipeline were to be applied in practice (e.g., remastering all textures of a game), one could also consider distributed training of models on big data platforms. There are frameworks for distributed deep learning on Hadoop/Spark, but often a dedicated GPU cluster using frameworks like PyTorch's Distributed Data Parallel or Horovod is used instead, due to communication efficiencies. Our work shows that at least for inference and evaluation, big data tools integrate fairly well.

X. Discussion of Results

The comparison between SRCNN and Real-ESRGAN on game imagery provides insights into the suitability of these models for different purposes. SRCNN, as a smaller model, could be more feasible for real-time applications on limited hardware (e.g., running on a game console in real-time at 60 FPS). It improves quality over naive scaling but does not fully recover all details. Real-ESRGAN, with its much higher complexity, achieves substantially better quality but at a computational cost. For offline processing of game assets (e.g., enhancing graphics for a re-release of a game), Real-ESRGAN is a superior choice, as our results indicate. The use of big data processing ensures that even if Real-ESRGAN is slow, one can process many images in parallel (for instance, batch-processing an entire archive of games overnight on a cluster).

From the big data perspective, this project validates that even for image processing tasks that involve heavy computation, the data-parallel model of Spark works well. The overhead of distributing deep learning inference is manageable and can be outweighed by the scaling benefits. One notable future improvement could be to integrate GPU usage in the Spark tasks. Apache Spark does not natively schedule GPU tasks, but with libraries like Nvidia RAPIDS or TensorFlowOnSpark, one could accelerate each task. This would marry the parallelism of big data with the speed of GPU acceleration, potentially enabling real-time or near-real-time processing of video streams with complex models. Another consideration is the network overhead of collecting images if we were to save outputs – in our case we only gathered metrics, which is a tiny amount of data (a few numbers per image). If the actual HR images (which are larger) need to be stored, writing them back to HDFS in parallel would be advisable to avoid funneling everything through the driver.

XI. Conclusion

This study compared two AI-based super-resolution models SRCNN and Real-ESRGAN for enhancing retro video game visuals within a big data processing pipeline. Contrary to expectations, SRCNN achieved higher average PSNR (33.08 dB) and competitive SSIM (0.9449) on 122 SuperTux screenshots, demonstrating strong performance despite its simpler architecture. Real-ESRGAN, while producing sharper and more visually appealing images, had lower PSNR but slightly higher SSIM on one test image, highlighting a trade-off between perceptual quality and pixel-level accuracy.

By integrating Hadoop and Spark, we also showed how super-resolution can be scaled efficiently for large datasets. Our pipeline enables fast and distributed processing, making it feasible to enhance entire game libraries or video content at scale.

In summary, SRCNN remains effective for structured content like game graphics, and with a scalable data pipeline, it can be deployed efficiently. This work demonstrates that even classic models can outperform more complex alternatives depending on the context and that combining machine learning with big data technologies offers a practical path toward large-scale visual enhancement.

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