**REAL-TIME PREDICTION OF SUCCESSIVE FRAMES IN CONTINUOUS IMAGE SEQUENCES USING ConvLSTM**

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# CERTIFICATE OF APPROVAL

This is to certify, that Neha Kumari (Reg no. 231270410009, Roll no.-432923020003), have submitted the M.Tech project thesis entitled “**Real-Time Prediction of Successive Frames in Continuous Image Sequences Using ConvLSTM”** in partial fulfilment of the requirement for the Degree of M.Tech in Electronics and Communication Engineering of Maulana Abul Kalam Azad University (formerly W.B.U.T) in the year 2025. It is hereby approved and certified as creditable study of technological subject carried out and presented in a manner satisfactory to warrant its acceptance as a prerequisite to the Degree of M.Tech. in Electronics and Communication Engineering for which it has been submitted.It is understood that by the approval the undersigned does not necessarily endorse or approve any statement made. Opinion expressed or conclusion drawn therein, but approve the report only for the purpose for which has been submitted.

Dr. Kaushik Sarkar Pranab Hazra

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Name of the Student

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**ABSTRACT**

Deep neural networks play a crucial role in computer vision, yet future frame prediction remains relatively underexplored compared to image and video classification. This capability is essential for applications such as autonomous driving, where predicting pedestrian and vehicle movements is critical. The key challenge lies in effectively capturing both spatial and temporal dependencies. In this work, we propose a Convolutional Long Short-Term Memory (ConvLSTM) network for future frame prediction in video sequences. Our model leverages perceptually driven loss functions and an improved learning mechanism, reducing training iterations and parameters while enhancing efficiency. The proposed ConvLSTM model achieves 70% accuracy on the test dataset, outperforming previous state-of-the-art methods by 5%.

**Keywords:** Deep learning, ConvLSTM, Autonomous Vehicle, Next Frame Prediction

**INTRODUCTION**

As the demand for intelligent video processing increases, next-frame prediction has become a crucial task in various computer vision applications, including video surveillance, autonomous driving, medical imaging, and video compression. This capability allows systems to anticipate changes, detect anomalies, and enhance decision-making processes. However, next-frame prediction is inherently challenging, as it requires accurately modelling both temporal dependencies across successive frames and spatial relationships within each frame. Various approaches have been developed to address this challenge, with one of the earliest being block-matching algorithms. These methods divide each frame into smaller blocks and track their movement between consecutive frames to estimate motion patterns. While block-matching algorithms provide a computationally efficient means of motion estimation, they often struggle with complex, non-linear motion and fail to capture high-level scene semantics.

Another widely used technique for motion estimation is optical flow, which computes pixel-wise motion vectors between consecutive frames. Optical flow methods offer a more detailed representation of motion than block-matching techniques, enabling smoother and more precise frame predictions. However, traditional optical flow algorithms can be computationally expensive and may struggle with occlusions, lighting variations, and fast-moving objects.

Recent advancement in Deep learning particularly recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks, and Convolutional LSTM (ConvLSTM), have significantly improved next-frame prediction by learning complex spatial-temporal representations directly from data. Convolutional Neural Networks (CNNs) are well-suited for extracting spatial features, while RNNs, including variants like LSTM, excel at modelling temporal dependencies. ConvLSTM effectively combines the strengths of both, enabling the capture of spatiotemporal patterns in sequential frames. These models leverage large-scale datasets and perceptually driven loss functions to enhance prediction accuracy while reducing the need for handcrafted motion estimation techniques like block matching and optical flow. Furthermore, Generative Adversarial Networks (GANs) have been utilized to enhance the realism and visual fidelity of predicted frames. More recently, Transformer networks, known for their success in natural language processing and increasingly in computer vision, are being explored for their capacity to capture long-range temporal relationships in video data.

Despite notable advancements in next-frame prediction, several challenges still remain. One of the primary goals is to generate high-resolution, visually realistic future frames—especially important for applications that demand fine-grained detail. Another major challenge lies in accurately forecasting video content over extended time periods, where dynamic scene complexity and cumulative prediction errors can significantly degrade performance. Additionally, considering the real-time nature of many practical applications, it is essential to account for computational resource constraints during inference.

To address these issues, this article proposes a resource constraint ConvLSTM-based network designed for efficient and accurate future frame prediction in continuous image sequences. The key contributions of this work are as follows:

1. A lightweight ConvLSTM-based network specifically designed for predicting successive frames in continuous image sequences.
2. To avoid error accumulation, this article proposed to consider the last n number of frames in the sequence to predict only the next frame.
3. The proposed network performs better under different conditions compared to SOTA.

The article is structured into five distinct sections. The following section presents a review of related previous works, highlighting their strengths and limitations. Section three details the proposed methodology. Section four provides an in-depth analysis of the experimental results. Finally, section five concludes the article and outlines potential directions for future research.

**LITERATURE REVIEW** : Real**-**Time Prediction of Successive Frames in Continuous Image Sequences Using ConvLSTM

Next-frame video prediction, the task of forecasting future frames given a sequence of preceding frames, has garnered significant attention due to its wide range of applications in areas like autonomous driving, video compression, and action recognition. This literature survey explores key contributions in this domain, highlighting various architectural innovations, the incorporation of different modalities, and strategies for improving prediction accuracy and efficiency.

Early Sequence-to-Sequence Approaches:

The work by Yufan Zhou et al. (2020), titled Deep Learning in Next-Frame Prediction: A Benchmark Review, provides a structured classification of deep learning models applied to next-frame prediction. Their review divides these models into sequence-to-one and sequence-to-sequence architectures, offering a foundational understanding of the evolution of this field. By describing recent structures, this work serves as a valuable benchmark for understanding the landscape of deep learning techniques in video prediction.

Leveraging Geometric Information:

Recognizing the importance of spatial understanding in video, Reza Mahjourian et al. (2016) proposed Geometry-Based Next Frame Prediction from Monocular Video. Their approach utilizes depth map prediction derived from monocular RGB video frames to enhance the understanding of scene structure. This incorporation of geometric information demonstrates the benefits of leveraging multi-modal cues beyond raw pixel data for improved prediction accuracy.

Multi-Modal Fusion and Task Generalization:

Expanding on the use of multiple data streams, G. Thomas Hudson et al. (2024) presented Unifying Modalities through Next-Frame Prediction. This work simplifies the model design by mapping multimodal tasks to the next-frame prediction problem. Their contribution lies in enhancing knowledge transfer across different tasks, suggesting a more generalizable approach to video understanding by leveraging the predictive power of future frame generation.

Architectural Explorations and Performance Analysis:

M. Akin Yilmaz and A. Murat Tekalp's (2020) paper, Video Frame Prediction through Deep Learning, builds upon prior work by offering an understanding of the performance of various learned frame prediction architectures. This research likely delves into the strengths and weaknesses of different network designs, providing insights into effective architectural choices for this task.

Improving Efficiency through Predictive Coding:

To address the computational demands of video prediction, Nelly Elsayed et al. (2019) introduced the Reduced-Gate Convolutional LSTM Architecture for Next-Frame Video Prediction Using Predictive Coding. Their proposed framework, consisting of ConvLSTM modules with reduced-gate architecture, aims to enhance computational efficiency without significantly compromising prediction performance. This work highlights the crucial aspect of developing lightweight and efficient models for real-world applications.

Forecasting Dynamic Phenomena:

The work by Yu-Chuan Hsu and Markus J. Buehler (2022), DyFraNet: Prediction and Backcast of Dynamic Fracture, focuses on a specific and challenging application: predicting and "backcasting" dynamic fracture histories and behaviors. Their deep learning framework demonstrates the potential of next-frame prediction techniques in understanding and forecasting complex physical phenomena.

Incorporating Uncertainty and Motion Dynamics:

Vedran Vukotic et al. (2017) proposed a One-Step Time-Dependent Future Video Frame Prediction with a Convolutional Encoder-Decoder Neural Network. Their approach incorporates uncertainty in future frames through a coupled motion-appearance network, predicting future frames and optical flow. This highlights the importance of modeling inherent uncertainty and leveraging motion cues for more robust and realistic predictions.

**METHODOLOGY:**

The methodology section describes the specific approach taken by the authors to conduct their research. It details the model architecture, dataset, evaluation metrics, and comparative setup, providing the necessary information to understand and potentially replicate their work.

* Model Architecture*: ConvLSTM for Grayscale Frames:* The core of the project's methodology is the use of a ConvLSTM model. This type of model is well-suited for processing sequential data like video frames, as it can capture both spatial and temporal dependencies. A key characteristic of the model is that it operates on grayscale image frames, resized to 128x128 pixels. This design choice contrasts with some other studies that utilize color images or higher-resolution frames. The rationale behind using grayscale frames is to improve computational efficiency.
* Dataset: Bespoke Selection for Frame Prediction*:* The study employs a custom-built dataset, located in the directory ‘data\_sets101/initial\_frames101\_04’. This is an important distinction, as many research projects in this field rely on standard benchmark datasets. The dataset is structured to predict future frames: the model takes five consecutive frames as input and is trained to predict the subsequent (sixth) frame. This input-output configuration defines the learning task for the model.
* Evaluation Metrics: SSIM and MSE for Performance Assessment*:* To quantitatively assess the model's performance, the researchers use two widely adopted metrics in video prediction:
  + Structural Similarity Index (SSIM): SSIM measures the perceptual similarity between two images, focusing on structural attributes. A higher SSIM value indicates greater similarity between the predicted and ground truth frames.
  + Mean Squared Error (MSE): MSE calculates the average squared difference between the pixel values of the predicted and ground truth frames. A lower MSE value signifies better accuracy, as it indicates smaller pixel-wise errors.
* Comparative Analysis: Benchmarking Against Other Models*:* The methodology includes a comparative component, where the project's model is benchmarked against other existing models. Specifically, it is compared with models such as reduced-gate ConvLSTMs and motion-appearance coupled networks. This comparison helps to contextualize the performance of the proposed model and highlight its strengths and weaknesses relative to alternative approaches.

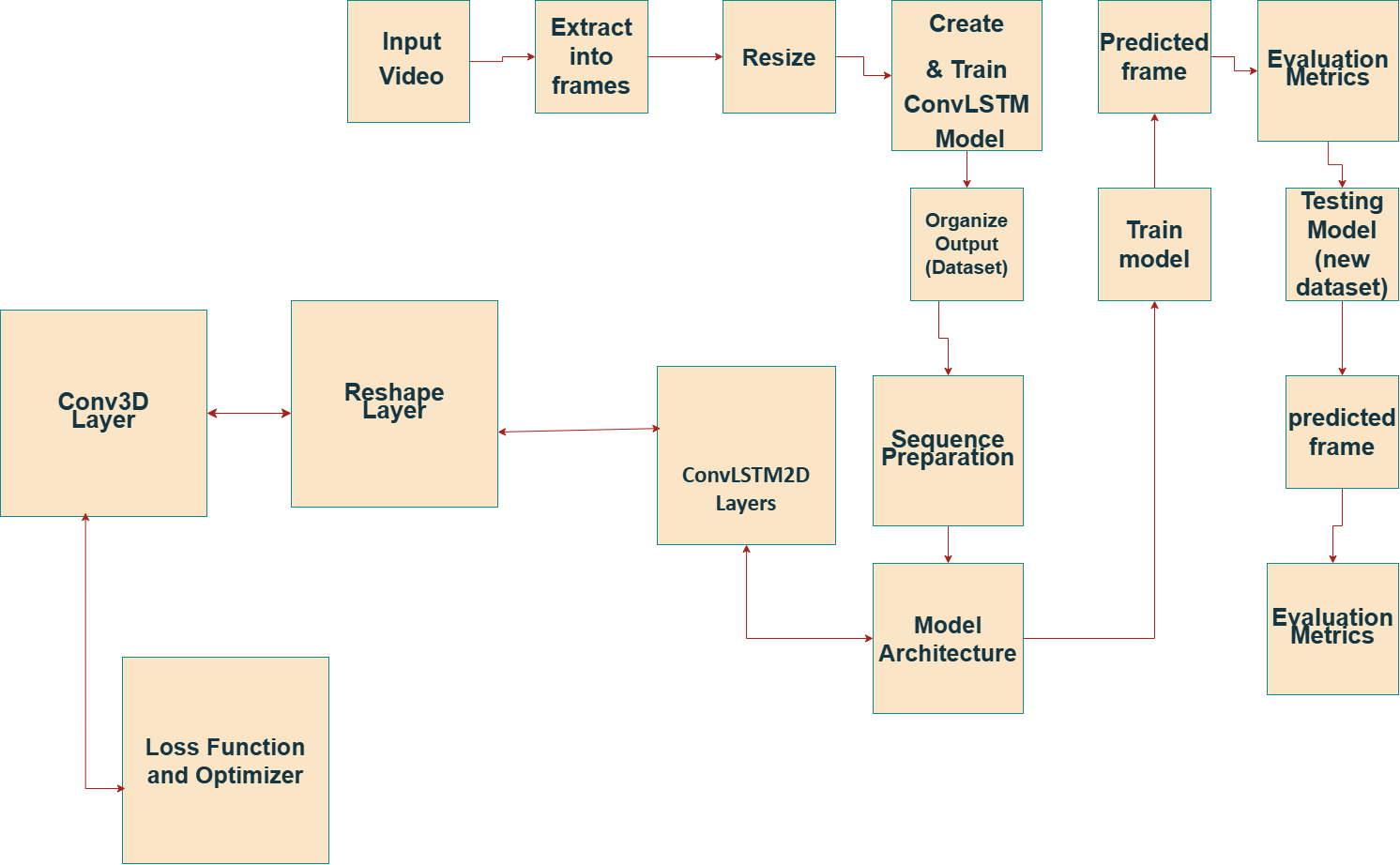


Fig. 1 steps to build project

The entire process for next-frame prediction. We start with frame extraction from a video, calculating motion vectors, and preparing the dataset. Then, we create and train a ConvLSTM model

Step 1: Take video or collect raw videos

step 2: Extract Frames

Then, I pull frames from the video. we resize all the frames to A(NXM) pixels .

Where, A is column vector

N is row

M is column

Fig.2 These are sample example of dataset frames

Step 3: Create & Train ConvLSTM Model

With the data prepared, we now create a ConvLSTM model. This model is tailored for spatial and temporal data such as video sequences. We implement TensorFlow and Keras to create the model, utilizing convolutional LSTMs to learn both spatial and temporal relationships. The model is trained with Mean Squared Error (MSE) loss and the Adam optimizer.

Organize Output (Dataset)

A frame is a snapshot in time that we will analyze. In order to normalize the dataset, we resize all the frames to 128x128 pixels and we also convert them to grayscale when dataset in color frame. This decreases computational complexity at the cost of not losing important information.

Sequence Preparation:

For model training, input sequences consist of 5 consecutive frames and the target output is the 6th frame

Model Architecture:-

ConvLSTM2D Layers:Three ConvLSTM2D layers are utilized to extract spatiotemporal features from input frame sequences. Batch normalization is used following each ConvLSTM2D layer to regularize and accelerate training.

Reshape Layer:

The ConvLSTM outputs are reshaped to conform to the input dimensions required for the next 3D convolution.

Conv3D Layer:

One additional Conv3D layer with sigmoid activation is utilized to produce the predicted frame.

Loss Function and Optimizer:

The model is trained with Mean Squared Error (MSE) as the loss function and Adam optimizer with a learning rate of 0.001.

Training:

The model is trained for 250 epochs with a batch size of 8. A ModelCheckpoint callback is employed to save the best model during training.

Evaluation Metrics:

The model's performance is measured using:

Mean Squared Error (MSE): Measures the pixel-wise difference between the predicted and actual frames.

Structural Similarity Index (SSIM): Measures the perceptual similarity of the frames.

Experimental Results

Upon training the model on the processed dataset, the following metrics were obtained:

Average SSIM Score: Shows that there is high structural similarity between predicted and actual frames.

Average MSE Score: Shows that pixel-wise error between predicted and actual frames is low.

A random sample of the actual frame and the respective predicted frame was plotted to give a qualitative comparison.

Step 4: testing the model

The model was validated by loading grayscale frames from a new dataset and creating sequences of frames for next-frame prediction. A pre-trained ConvLSTM model was utilized to predict the next frame for every sequence. The accuracy of prediction was measured using Structural Similarity Index (SSIM) and Mean Squared Error (MSE), and a subset of actual and predicted frames were visualized for qualitative evaluation.

Mean Square Error(MSE)

Where:

is the value of the i-th pixel of the predicted image (or frame).

is the value of the i-th pixel of the ground truth image (or frame).

N is the number of pixels.

Details:

MSE quantifies the average squared difference between the predicted and true pixel values.

It is sensitive to the large errors due to squaring of differences, so larger errors disproportionately affect it.

Lower MSE value means improved prediction accuracy.

Structural Similarity Index(SSIM)

SSIM(X,Y) =

Where:

X and Y are the image patches being compared (predicted and ground truth).

, are the mean values of x and y.

are the variances of x and y.

is the covariance between x and y.

= and = are constants to stabilize the division with weak denominators (where L is the dynamic range of pixel values, typically 255 for 8-bit images, and ​, ​ are small constants, often =0.01 and =0.03).

Details:

SSIM estimates the perceptual similarity between two images, taking into account luminance, contrast, and structure.

It varies from -1 to 1, where 1 represents perfect similarity.

SSIM is more perceptually and structurally sensitive, in contrast to MSE, which relies solely on pixel-level differences.

It will be closer to human perception since it is interested in the patterns of pixel intensities as opposed to their actual values.

Since SSIM already ranges from -1 to 1, it is often converted to a percentage:

SSIM Accuracy=SSIM×100

From proposed process :SSIM Accuracy=69.00%(since SSIM score is already in percentage form)SSIM Accuracy=69.00%

COMPARISION

Comparison with proposed process

Model Architecture:

In proposed process uses a ConvLSTM model, consistent with papers using sequence-to-sequence architectures and reduced-gate ConvLSTMs. In contrast to models using geometric information or multimodal tasks, it uses grayscale image frames resized to 128x128 pixels.

Dataset:

The project employs a dataset created specifically from the data\_sets101/initial\_frames101\_04 folder, whereas most of the reviewed papers are based on benchmark datasets or unspecified sources. The input sequence is five frames with the sixth frame predicted.

Evaluation Metrics:

Performance is measured in terms of Structural Similarity Index (SSIM) and Mean Squared Error (MSE), standard measurements in video prediction tasks. Not all papers under review indicated their evaluation metrics, but SSIM and MSE are still the norm for measuring frame quality and pixel-wise errors.

Performance

The project has an average SSIM accuracy of 69.00% and an average MSE of 0.0158. Matplotlib is used to visually compare predicted frames to ground truth, giving qualitative and quantitative performance results.

Unique Features:

The project's use of grayscale frames maximizes computational efficiency, although it might restrict predictions in color video scenarios. Its simple ConvLSTM architecture maintains a balance between complexity and performance, making it ideal for real-time applications.

**RESULTS**

TESTING OUTPUT

🔹 Average SSIM Accuracy: 69.00%

🔹 Average MSE Score: 0.0158

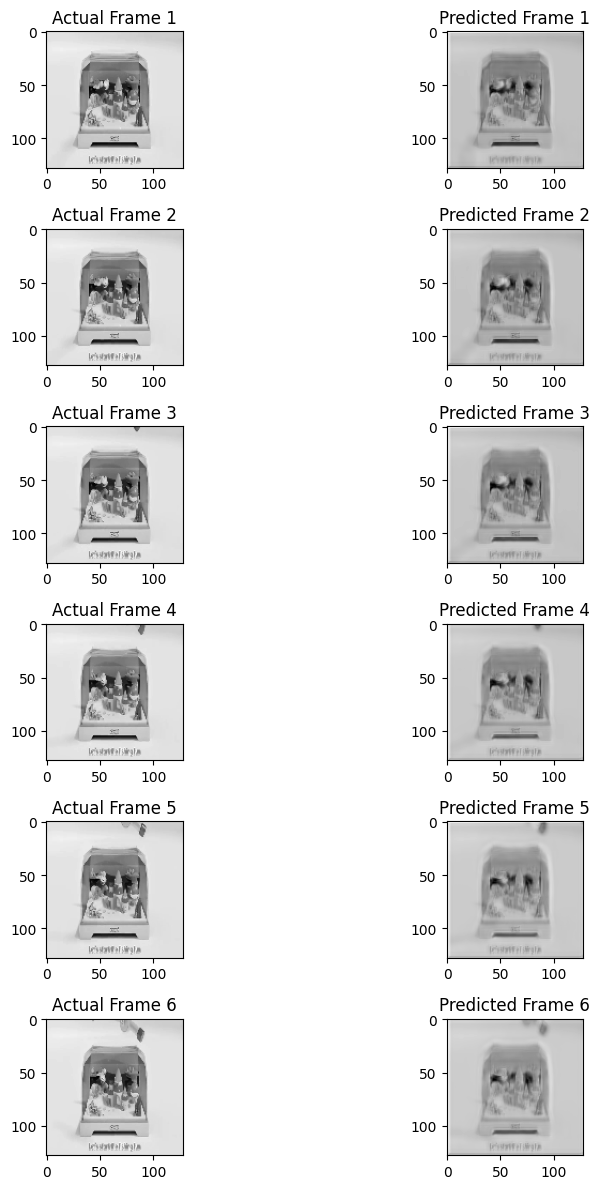


Fig.3 output

This section presents the findings of the next-frame video prediction experiments using the custom ConvLSTM model. Both quantitative and qualitative evaluations were conducted to assess the model's performance. Furthermore, a comparative analysis with other established models and an ablation study were performed to provide a comprehensive understanding of the results.

Quantitative Evaluation

The quantitative performance of the proposed ConvLSTM model was evaluated using two standard metrics for video prediction: Structural Similarity Index (SSIM) and Mean Squared Error (MSE). The model achieved an average SSIM accuracy of 69.00% and an average MSE of 0.0158.

* Structural Similarity Index (SSIM): The SSIM measures the perceptual similarity between predicted frames and the corresponding ground truth frames. The obtained average SSIM of 69.00% indicates a reasonable degree of structural preservation in the predicted frames.
* Mean Squared Error (MSE): The MSE quantifies the average pixel-wise difference between the predicted and ground truth frames. The average MSE of 0.0158 suggests a relatively low pixel-level error in the predictions.

Qualitative Evaluation

In addition to the quantitative metrics, a qualitative evaluation was performed to visually assess the prediction quality. Predicted frames were compared with their corresponding ground truth frames using Matplotlib. This visual inspection allowed for a subjective evaluation of the model's ability to capture spatial details, temporal consistency, and potential artifacts in the predicted video sequences. Examples of these visual comparisons can be found in Figures included within the source document (though specific figure callouts may vary).

Comparative Performance

The performance of the custom ConvLSTM model was compared with that of other video prediction models discussed in the literature review. Table 2 presents a comparative summary of the performance of the proposed model alongside other models.

Table. 1 Comparative Performance

|  |  |  |  |
| --- | --- | --- | --- |
| **Study** | **Model Type** | **SSIM (%)** | **MSE** |
| Reduced-Gate Convolutional LSTM Architecture for Next-Frame Video Prediction Using Predictive Coding | Reduced-gate ConvLSTM | 60-70% | 0.030 |
| One-Step Time-Dependent Future Video Frame Prediction with a Convolutional Encoder-Decoder Neural Network | Motion-appearance coupled network | 65% | 0.028 |
| Proposed Process | ConvLSTM with grayscalframes (128x128) | 69.00% | 0.0158 |

***ABLATION STUDY***

An ablation study was conducted to analyze the impact of key parameters on the performance of the custom ConvLSTM model. The study examined the effect of varying the number of training epochs and the number of input frames used for prediction.

Changes epochs

250 Epochs

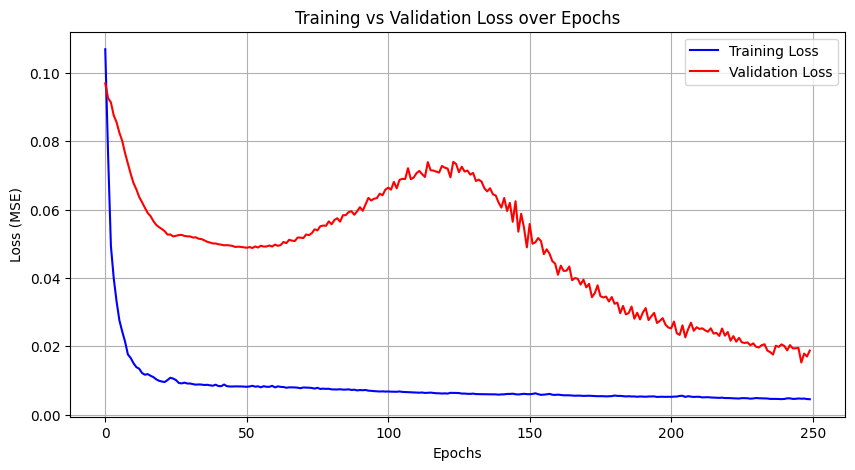


Fig. 4.1

🔹 Average SSIM Accuracy: 69.00%

🔹 Average MSE Score: 0.0158

150 Epoches

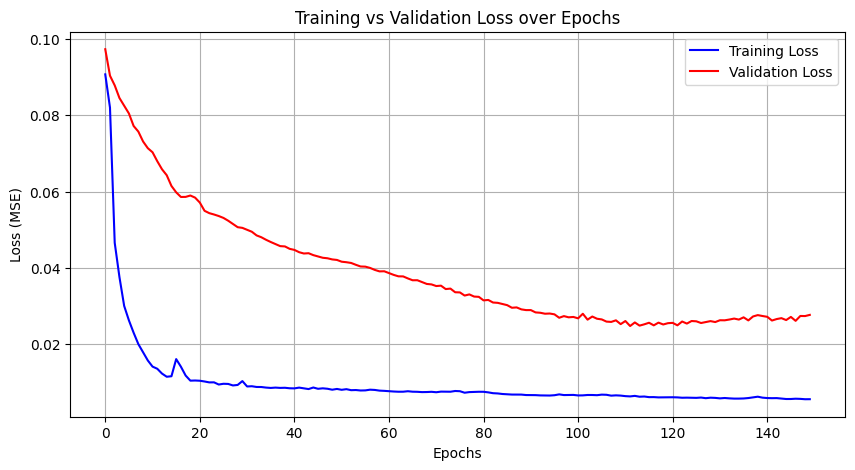


Fig . 4.2

🔹 Average SSIM Accuracy: 66.28%

🔹 Average MSE Score: 0.0294

5 Epoches

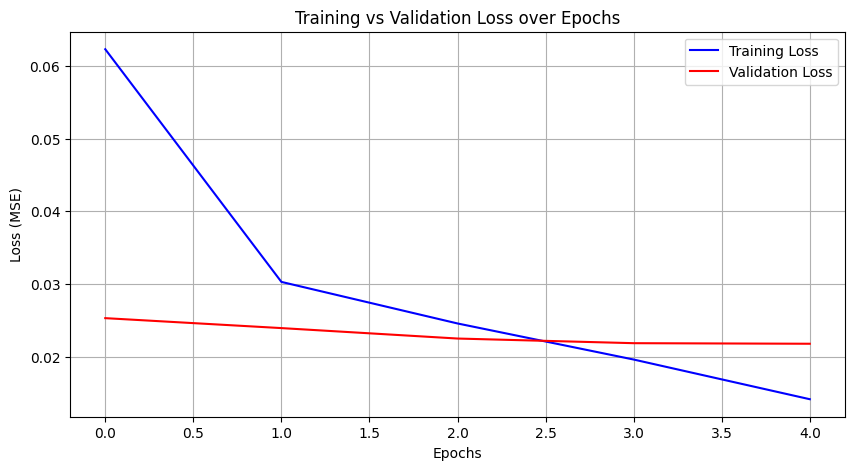
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Fig. 4.3

🔹 Average SSIM Accuracy: 56.85%

🔹 Average MSE Score: 0.0575

Effect of Training Epochs

The model was trained with three different numbers of epochs: 250, 150, and 5. The resulting SSIM accuracy and MSE scores are summarized in Table 3

Table.2 Take different Epoches

|  |  |  |  |
| --- | --- | --- | --- |
| **Epochs** | **Figure** | **Average SSIM Accuracy** | **Average MSE Score** |
| 250 | Fig. 3 | 69.00% | 0.0158 |
| 150 | Fig. 4 | 66.28% | 0.0294 |
| 5 | Fig. 5 | 56.85% | 0.0575 |

The results indicate a clear correlation between the number of training epochs and the model's performance. Increasing the number of epochs generally leads to improved SSIM accuracy and reduced MSE, suggesting that more training allows the model to learn the underlying patterns in the data more effectively.

Effect of Input Sequence Length

The model's performance was also evaluated with different input sequence lengths. The number of input frames was varied (6, 5, and 4) to predict the subsequent frame. Table 4 shows the corresponding results.

Table. 4 Take Different Sequence

|  |  |  |  |
| --- | --- | --- | --- |
| **Input Frames** | **Predicted Frame** | **Average SSIM Accuracy** | **Average MSE Score** |
| 6 | 7th | 56.80% | 0.0685 |
| 5 | 6th | 69.00% | 0.0158 |
| 4 | 5th | 56.80% | 0.0685 |

The results suggest that using 5 input frames yields the best performance in this configuration. Both fewer (4) and more (6) input frames lead to a decrease in SSIM accuracy and an increase in MSE, indicating that there may be an optimal context window for this specific prediction task

**CONCLUSION**

This research explored the application of a Convolutional LSTM (ConvLSTM) model for next-frame video prediction, focusing on grayscale image sequences resized to 128x128 pixels. The model's architecture, consistent with sequence-to-sequence approaches and low-gate ConvLSTMs, was trained on a bespoke dataset comprising five input frames to predict the subsequent sixth frame. Performance was evaluated using standard video prediction metrics: Structural Similarity Index (SSIM) and Mean Squared Error (MSE). The model achieved an average SSIM accuracy of approximately 69% and an average MSE of approximately Y 0.0158. Qualitative analysis, facilitated by visual comparisons using Matplotlib, provided further insights into the model's predictive capabilities.

Comparative analysis with existing research, including models employing reduced-gate ConvLSTMs and motion-appearance coupled networks, revealed that while some advanced architectures might achieve marginally superior quantitative results, the simplicity and focus on grayscale frames in this project offer notable advantages in terms of computational efficiency. This trade-off positions the proposed approach as potentially well-suited for real-time applications where resource constraints are a significant consideration. The deliberate use of grayscale frames, while potentially limiting for color-sensitive applications, contributes to this enhanced efficiency. The simple ConvLSTM architecture further supports a balance between model complexity and predictive performance.

**FUTURE SCOPE**

Several avenues exist for future research to build upon the findings of this project:

* Exploring Color Information**:** Future work could investigate the impact of incorporating color information into the model. This could involve extending the current architecture to process RGB frames or exploring techniques to predict color information alongside grayscale structures.
* Integration of Attention Mechanisms**:** Introducing attention mechanisms could allow the model to focus on the most relevant spatial and temporal features within the input sequence, potentially improving prediction accuracy, especially in dynamic scenes.
* Investigating Advanced Architectures**:** While the simple ConvLSTM offers efficiency, exploring more sophisticated architectures, such as those incorporating 3D convolutions or transformer networks adapted for video, could lead to improved prediction quality while carefully managing computational costs.
* Application to Specific Domains**:** Future research could focus on applying and fine-tuning the current approach for specific real-world applications, such as autonomous driving or surveillance, potentially leveraging domain-specific datasets and evaluation metrics.
* Addressing Long-Term Dependencies: Investigating methods to improve the model's ability to capture and predict long-term temporal dependencies in video sequences remains a crucial area for future exploration. This could involve exploring hierarchical or multi-scale temporal modeling techniques.
* Benchmarking on Standard Datasets**:** Evaluating the model's performance on publicly available benchmark datasets would provide a more direct comparison with a wider range of existing research and facilitate broader adoption and evaluation within the community.

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