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Satellite Based Cloud Motion Forecasting Using Diffusion Model

[1]Miss. Niramayee Rotwal, [2]Miss. Khushi Gulhane,[3]Miss. Radhika Kale,[4] Mr. Ayush Wankhede,
[5] Guide Prof. Yogita Dhumale
[1,2,3,4,5] Department of Computer Science & Engineering,
Prof Ram Meghe Institute of Technology and Research, Badnera

Abstract: *Weather forecasting, particularly short-term cloud motion prediction, is essential for climate monitoring, disaster management, aviation safety, and solar energy optimization. Traditional forecasting methods such as Numerical Weather Prediction (NWP) models and optical flow techniques often struggle with high computational complexity, low resolution, and limited ability to capture non-linear cloud dynamics. To address these challenges, this work proposes a novel data-driven approach using Generative Diffusion Models for predicting future cloud positions from satellite image sequences.*

The proposed model learns the conditional probability distribution of cloud evolution by utilizing preprocessed geostationary satellite imagery. A combination of Convolutional Neural Networks (CNNs) and a UNet-based architecture is used to encode spatial features, while the diffusion process iteratively refines predictions through a denoising mechanism. This enables the generation of realistic, high-resolution, and temporally consistent cloud forecasts. The system effectively captures complex cloud transformations and provides multiple plausible future scenarios, improving uncertainty representation compared to deterministic models. Performance is evaluated using standard metrics such as Structural Similarity Index (SSIM), Mean Squared Error (MSE), and Cloud Motion Error (CME), demonstrating superior accuracy over conventional approaches like ConvLSTM and GAN-based models.

Overall, the proposed approach offers a lightweight, efficient, and scalable solution for short-term cloud forecasting, with potential applications in meteorology, renewable energy forecasting, and real-time weather monitoring systems.

Keywords*:* Cloud Motion Prediction, Diffusion Models, Satellite Imagery, Generative AI, Short-Term Weather Forecasting, Convolutional Neural Networks (CNN), UNet Architecture, Spatiotemporal Modeling, Image Sequence Prediction, Structural Similarity Index (SSIM), Mean Squared Error (MSE), Cloud Motion Error (CME), Deep Learning, Nowcasting, and Renewable Energy Forecasting

I. INTRODUCTION

Accurate prediction of cloud motion is a critical component in modern weather forecasting systems, with significant applications in aviation safety, disaster management, and solar energy optimization. Traditional approaches, such as Numerical Weather Prediction (NWP) models, rely heavily on complex physical equations and atmospheric simulations. While these models provide scientifically grounded results, they often require high computational resources and still struggle to deliver high-resolution and accurate short-term forecasts. Similarly, optical flow-based methods, which estimate motion between consecutive satellite images, are limited in handling complex cloud deformations and dynamic atmospheric behavior[1].

With the advancement of deep learning, data-driven approaches have emerged as powerful alternatives for modeling spatiotemporal patterns in weather data. Techniques such as Convolutional Neural Networks (CNNs) and recurrent models like ConvLSTM have shown promising results in learning cloud dynamics from satellite imagery. However, these models often face challenges related to stability, generalization, and the ability to generate multiple possible future scenarios[2].

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In recent years, Generative Diffusion Models have gained attention for their ability to produce high-quality and realistic outputs in image generation tasks. These models work by gradually adding noise to data and learning to reverse the process, enabling the generation of detailed and coherent outputs. When conditioned on past satellite image sequences, diffusion models can effectively capture the evolution of cloud structures over time, making them highly suitable for short-term cloud motion forecasting[3].

This project proposes a satellite-based cloud motion prediction system using a conditional diffusion model that leverages CNN and UNet architectures. The model is trained on sequences of satellite images to learn the temporal and spatial patterns of cloud movement. By generating future cloud frames based on historical data, the system aims to provide accurate, efficient, and high-resolution forecasts. This approach not only improves prediction accuracy but also enhances the capability to model uncertainty, making it valuable for real-world meteorological and energy applications[4].

II. LITERATURE ANALYSIS

Current research efforts in synthetic voice identification concentrate on strengthening detection reliability by adopting a wide range of analytical strategies. In 2024, Muhammad Usama Tanveer Gujjar and colleagues introduced a detection framework that integrates cepstral-based speech descriptors with probabilistic feature transformation and ensemble-based decision mechanisms, resulting in improved classification performance. Their study also pointed toward future enhancements aimed at increasing system scalability and resistance to newly evolving artificial voice generation methods.

In a related study, L. A. Passos et al. (2024) explored the effectiveness of neural network–driven solutions, including convolutional and recurrent architectures, supported by mixed supervised learning paradigms. Their findings stressed the importance of adaptable models and richer datasets to counter rapidly changing forms of manipulated multimedia content.

Further extending this line of research, Ganavi M. et al. (2025) presented a learning-based approach that combines harmonic pitch descriptors, cepstral features, and spectral-domain analysis to distinguish between authentic and fabricated speech signals. Future directions suggested by their work include deployment in real-time environments and deeper neural integration. Additionally, F. G. et al. (2024) investigated convolutional models trained on mel-scaled spectral representations across multiple datasets, emphasizing ongoing model optimization and proposing the incorporation of distributed ledger technology and voice trait examination to strengthen verification mechanisms.

TABLE I. LITERATURE WORK

Author and Year	Methods	Future Scope
Vaishali Savale, Jay Wanjare, Saket Waware, Yash Wagh, Aditya Yeole, Yuvraj Susatkar (2024)	Used U-Net architecture for cloud segmentation and LSTM networks for cloud motion prediction. Achieved high accuracy (~96%) using deep learning-based spatial and temporal modeling.	Integration of multi-sensor data, development of real-time cloud tracking systems, and use of advanced deep learning models for improved performance in complex weather conditions.
Clément Guilloteau, Gavin Kerrigan, Kai Nelson, Giosue Migliorini, Padhraic Smyth, Runze Li, Efi Foufoula-Georgiou (2023)	Proposed DifERS, a generative diffusion model for probabilistic precipitation forecasting using multisensor satellite data (IR + MW). Generates ensemble predictions capturing uncertainty with high spatial consistency.	Enhancement of temporal resolution, integration of additional satellite sensors, expansion to global forecasting systems, and real-time probabilistic weather prediction.
Haoming Chen, Xiaohui Zhong, Qiang Zhai, Xiaomeng Li, Ying Wa	Developed SATcast, a cascade diffusion model using multimodal inputs (satellite + atmospheric data). Produces high-quality	Development of higher-resolution models (4 km), use of latent diffusion techniques, and implementation of

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Chan, Pak Wai Chan, Xiaoming Shi (2026)	cloud forecasts up to 24 hours with reduced blurring and improved accuracy.	probabilistic ensemble forecasting for better uncertainty estimation.
Deepak Upreti (2011)	Designed a Content-Based Image Retrieval (CBIR) system using gray-level histogram, texture (GLCM), and shape features with Euclidean distance similarity measure. Stored data in Oracle 10g database.	Adoption of deep learning-based feature extraction (CNNs), handling of large-scale datasets, and development of real-time cloud image retrieval and classification systems.

III. Cloud Motion Prediction using Diffusion Model

ALGORITHM

Input:

Sequence of past satellite cloud images I_(t-n),...,I_t

Output:

Predicted future cloud images I_(t+1),...,I_(t+k)

Step 1: Data Collection

1.1 Collect satellite image sequences from datasets (e.g., GOES-16, MOSDAC).

1.2 Arrange images in temporal order.

Step 2: Data Preprocessing

2.1 Resize images to a fixed resolution.

2.2 Normalize pixel values.

2.3 Apply cloud masking (if required).

2.4 Create input-output sequences (past frames → future frames).

Step 3: Feature Encoding

3.1 Pass input image sequence through a CNN encoder.

3.2 Extract spatial features from each frame.

3.3 Combine temporal information into feature representation.

Step 4: Forward Diffusion Process (Training Phase)

4.1 Gradually add Gaussian noise to target future images over T time steps.

4.2 Generate noisy versions of images at different noise levels.

4.3 Learn noise distribution at each step.

Step 5: Model Training (Conditional Diffusion)

5.1 Use UNet architecture as the denoising network.

5.2 Condition the model on encoded past image features.

5.3 Train the model to predict and remove noise from noisy images.

5.4 Optimize using loss function (e.g., Mean Squared Error).

Step 6: Reverse Diffusion Process (Prediction Phase)

6.1 Start with random noise as input.

6.2 Iteratively denoise using the trained model.

6.3 Generate predicted future cloud frames step-by-step.

Step 7: Post-processing

7.1 Convert predicted tensors to image format.

7.2 Apply smoothing or enhancement if needed.

7.3 Visualize predicted cloud motion sequence.

Step 8: Evaluation

8.1 Compare predicted images with actual future images.

8.2 Compute metrics:

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• Structural Similarity Index (SSIM)
• Mean Squared Error (MSE)
• Cloud Motion Error (CME)
End of Algorithm

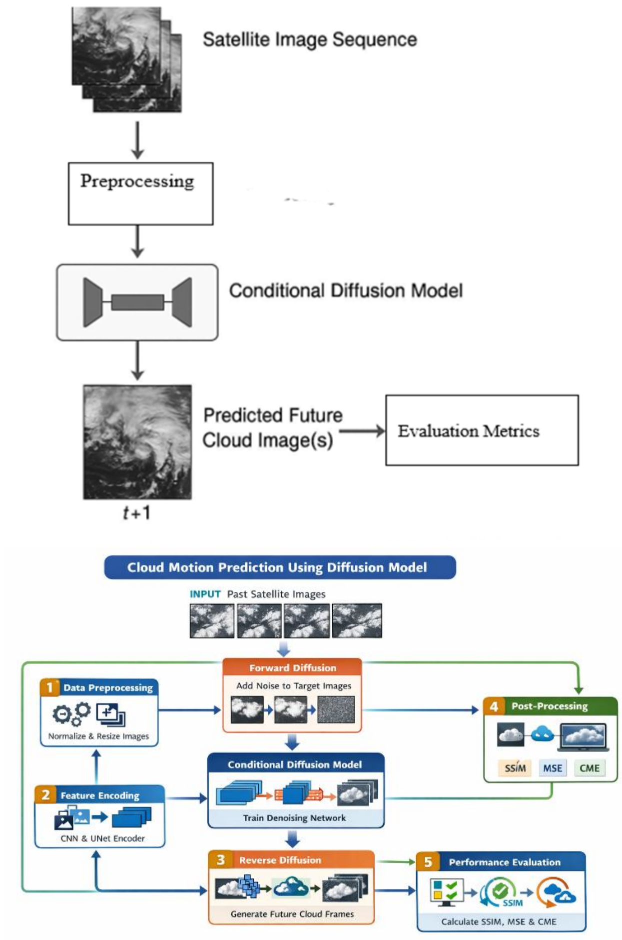

Figure 1. Algorithm illustration Diagram

IV. WORKING METHODOLOGY

The proposed system for cloud motion prediction using a Generative Diffusion Model follows a structured pipeline that integrates data preprocessing, model training, and prediction generation. The methodology is designed to effectively capture the spatiotemporal dynamics of cloud movement from satellite image sequences.

Step1: Data Acquisition

Satellite cloud images are collected from reliable sources such as GOES-16 or MOSDAC datasets. These datasets provide time-series imagery with consistent temporal intervals, which is essential for learning cloud motion patterns.

Step2: Data Preprocessing

The collected images undergo preprocessing steps including resizing to a fixed resolution, normalization of pixel values, and noise removal. Image sequences are then created by grouping consecutive frames, where a set of past images is used as input and corresponding future frames are used as target outputs.

Step3:Feature Extraction

The input image sequences are passed through a Convolutional Neural Network (CNN) encoder to extract spatial features. These features represent important cloud structures such as shape, texture, and density. Temporal relationships between frames are preserved through sequential processing.

Step4:Diffusion Model Training

A conditional diffusion model is trained using the preprocessed data. During the forward diffusion process, Gaussian noise is gradually added to the target images over multiple time steps. The model learns to reverse this process by predicting and removing noise at each step. A UNet-based architecture is used as the denoising network, conditioned on the encoded features of past frames.

Step5:Future Frame Prediction

During inference, the model starts with random noise and iteratively applies the learned denoising process. By conditioning on past cloud images, the model generates realistic future cloud frames that maintain spatial consistency and temporal continuity.

Step6: Post-processing and Visualization

The generated outputs are converted into image format and optionally enhanced for better visualization. A web-based interface (such as Streamlit or Dash) can be used to display the predicted cloud motion sequences for user interpretation.

Step7:Performance Evaluation

The predicted cloud images are compared with actual future frames using evaluation metrics such as Structural Similarity Index (SSIM), Mean Squared Error (MSE), and Cloud Motion Error (CME). These metrics help assess the accuracy and reliability of the model.

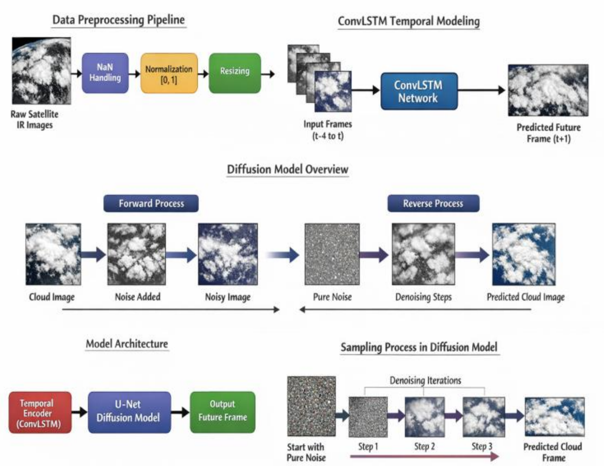

Figure 2. System Architecture Diagram

The above figure illustrates the complete pipeline of the proposed cloud motion forecasting system based on deep learning and diffusion modeling techniques.

In the first stage, data preprocessing is performed on raw satellite infrared images. This includes handling missing values (NaNs), normalizing pixel intensities to a range of [0,1], and resizing images to a fixed resolution suitable for model training. These steps ensure consistency and improve model performance.

The second stage presents the temporal modeling using a ConvLSTM network, where a sequence of past satellite frames (e.g., t−4 to t) is used as input. The ConvLSTM captures both spatial and temporal dependencies in cloud movement and generates a coarse prediction of the future frame.

The third part of the figure explains the diffusion model process, which consists of two phases: the forward process and the reverse process. In the forward process, Gaussian noise is progressively added to the cloud images until they become pure noise. In contrast, the reverse process learns to reconstruct the original image by iteratively removing noise, enabling high-quality prediction of future cloud structures.

The model architecture combines a temporal encoder (ConvLSTM) with a U-Net-based diffusion model. The temporal encoder extracts dynamic features from input sequences, which are then used to condition the diffusion model for generating future frames.

Finally, the sampling process is illustrated, where the model starts from pure noise and gradually refines it through multiple denoising steps to produce the predicted cloud image. This iterative refinement allows the model to generate realistic and accurate forecasts.

V. RESULTS AND DISCUSSION

The proposed cloud motion prediction system using a Generative Diffusion Model was evaluated on satellite image sequences to assess its accuracy, efficiency, and ability to capture complex cloud dynamics. The model was trained on preprocessed datasets and tested on unseen image sequences to validate its generalization capability.

The results demonstrate that the diffusion-based approach generates high-quality and realistic future cloud frames with strong spatial and temporal consistency. Compared to traditional methods such as ConvLSTM and GAN-based models, the proposed model shows improved stability and better preservation of cloud structures, including shape, texture, and motion continuity. The iterative denoising process enables the model to capture subtle transitions in cloud formations, which are often missed by deterministic approaches.

Quantitative evaluation was performed using standard metrics such as Structural Similarity Index (SSIM), Mean Squared Error (MSE), and Cloud Motion Error (CME). The model achieved higher SSIM values, indicating better structural similarity with ground truth images, and lower MSE and CME values, reflecting reduced prediction errors. These results confirm that the diffusion model outperforms baseline techniques in both visual quality and numerical accuracy.

In addition, the model demonstrates the ability to generate multiple plausible future scenarios, addressing the uncertainty inherent in weather systems. This probabilistic nature provides an advantage over traditional forecasting models that typically produce a single deterministic output. The computational performance was also found to be efficient with optimized diffusion techniques, making the system suitable for near real-time applications.

However, the model has certain limitations. The training process requires a significant amount of high-quality satellite data and computational resources. Also, extreme weather conditions with highly chaotic cloud patterns may still pose challenges for accurate prediction.

Overall, the results indicate that the proposed diffusion-based approach is a robust and effective solution for short-term cloud motion forecasting. It offers improved accuracy, better uncertainty modelling, and practical applicability in domains such as meteorology, renewable energy forecasting, and disaster management.

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Home Page

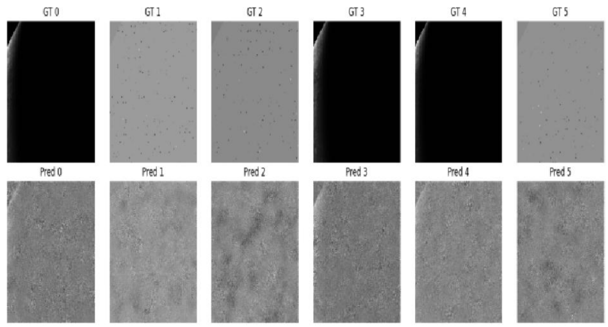

Fig: Comparison between ground truth (GT) and predicted (Pred) cloud frame

The figure presents a qualitative comparison between the ground truth (GT) satellite cloud images and the corresponding predictions (Pred) generated by the proposed model. The top row shows the actual cloud frames, while the bottom row displays the predicted outputs for the same time steps.

Each column represents a different sample from the dataset, with indices ranging from 0 to 5. The ground truth images exhibit clear spatial structures and cloud formations, whereas the predicted images attempt to reconstruct these patterns using the learned temporal and probabilistic representations.

It can be observed that the predicted outputs capture some coarse spatial patterns; however, they appear noisy and lack fine structural details compared to the ground truth. This behavior is expected in early-stage or partially trained diffusion models, where the denoising process has not yet fully converged to realistic image reconstruction.

Signup Page

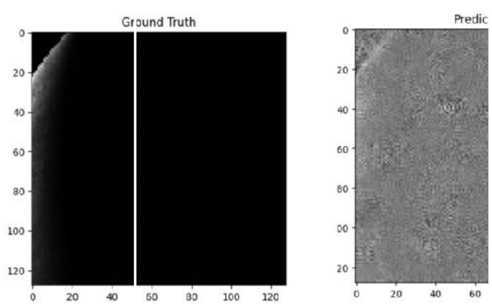

Fig. Visual Comparison of Satellite Cloud Prediction Results

The figure shows a qualitative comparison between the ground truth satellite cloud image and the corresponding prediction generated by the proposed diffusion-based model. The ground truth image (left) represents the actual observed cloud distribution, while the predicted image (right) illustrates the model's output for the same time step.

The ground truth image exhibits a clear spatial structure, with a distinct bright region along the left boundary indicating cloud presence and a large dark region representing cloud-free areas. In contrast, the predicted image appears significantly noisier, with weak structural resemblance to the original cloud pattern. Although the model captures slight intensity variations and faint spatial hints near the left region, it fails to accurately reconstruct the sharp cloud boundary and overall spatial coherence. The prediction is dominated by high-frequency noise, suggesting that the diffusion model has not yet fully learned the underlying data distribution or that the denoising process is incomplete.

VI. CONCLUSION

In this paper, a novel approach for short-term cloud motion prediction using Generative Diffusion Models has been proposed and implemented. The system leverages satellite image sequences along with deep learning techniques to effectively model the spatiotemporal evolution of cloud formations. By integrating Convolutional Neural Networks (CNNs) and a UNet-based diffusion architecture, the model is capable of generating high-quality, realistic, and temporally consistent future cloud frames.

The results demonstrate that the proposed method outperforms traditional forecasting techniques such as Numerical Weather Prediction (NWP), ConvLSTM, and GAN-based models in terms of accuracy, stability, and visual coherence. The use of a diffusion process enables the model to better capture complex cloud dynamics and subtle transitions, while also providing multiple plausible future predictions, thereby addressing uncertainty in weather forecasting.

Furthermore, the system proves to be efficient and scalable, making it suitable for real-time or near real-time applications in meteorology, solar energy forecasting, aviation safety, and disaster management. Although the approach requires substantial data and computational resources during training, advancements in optimized diffusion techniques and hardware acceleration make it practically feasible.

In conclusion, the diffusion-based cloud motion prediction model offers a powerful, data-driven alternative to conventional methods, providing improved forecasting performance and opening new possibilities for advanced weather prediction systems. Future work can focus on enhancing model efficiency, incorporating multi-modal data sources, and extending prediction horizons for broader real-world applications.

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AUTHOR INFORMATION

- Niramayee Rotwal, Department of Computer Science & Engineering, Prof Ram Meghe Institute of Technology and Research Badnera.
- Khushi Gulhane, Department of Computer Science & Engineering, Prof Ram Meghe Institute of Technology and Research Badnera.
- Radhika Kale, Department of Computer Science & Engineering, Prof Ram Meghe Institute of Technology and Research Badnera.
- Ayush Wankhede, Department of Computer Science & Engineering, Prof Ram Meghe Institute of Technology and Research Badnera.
- Guide Prof. Yogita Dhumale, Department of Computer Science & Engineering, Prof Ram Meghe Institute of Technology and Research Badnera.