A Hybrid Spatial Fuzzy Inference and CNN Approach for Forecasting Changes in Remote Sensing

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Abstract: Satellite images, captured by Earth observation satellites, provide crucial information for weather forecasting, aviation, natural resource management, and disaster response. This study presents a novel method for detecting changes in satellite cloud images, combining convolutional neural networks (CNNs) for feature extraction with a spatial complex fuzzy inference system (CFIS). The CNNs effectively capture color channel features in the image blurring and deblurring processes, while the CFIS models the spatiotemporal relationships in the data. Experiments conducted on a US Navy satellite image dataset demonstrate the effectiveness and stability of our proposed method, outperforming related studies concerning of R-squared (R2) and root mean square error (RMSE) measures.

Keywords: *Convolutional neural networks, Spatial complex fuzzy inference system, change detection, Remote sensing images*

Tiêu đề: **Hướng tiếp cận kết hợp giữa hệ suy diễn mờ phức không gian với mô hình CNN trong dự báo biến đổi trên ảnh vệ tinh**

Tóm tắt: Ảnh vệ tinh được chụp khi quan sát trái đất có thể cung cung cấp rất nhiều thông tin quan trọng về thời tiết dự báo, hàng không, quản lý tài nguyên thiên nhiên và ứng phó thiên tai. Nghiên cứu này trình bày một phương pháp mới áp dụng cho bài toán phát hiện thay đổi trong ảnh vệ tinh, sử dụng kết hợp mạng thần kinh tích chập (CNN) với hệ suy diễn mờ phức không gian (Spatial CFIS). Trong đó, mô hình CNN được sử dụng trong cả quá trình trích chọn thuộc tính theo từng kênh màu để tiến hành quá trình mờ hóa, quá trình giải mờ. Còn mô hình hệ suy diễn mờ phức không gian có nhiệm vụ mô hình hóa các mối quan hệ không gian và thời gian trong dữ liệu để sinh bộ luật. Thực nghiệm được tiến hành trên Bộ dữ liệu ảnh vệ tinh của Hải quân Hoa Kỳ cũng đã chứng minh tính hiệu quả, ổn định của mô hình đề xuất của chúng tôi so với các phương pháp nghiên cứu liên quan trên cả hai độ đo đánh giá trung bình của các sai số bình phương (RMSE) và độ đo tương quan R bình phương (R2).

Từ khóa: *Mạng thần kinh tích chập, hệ suy diễn mờ phức không gian, biến đổi ảnh, ảnh vệ tinh*

I. INTRODUCTION

As an advanced technique, Remote sensing (RS) platforms are increasingly adept at gathering diverse data, which has become invaluable for environmental monitoring and tracking climate change through satellite image analysis. Change detection (CD), the procedure of detecting alterations within the same geographical area across different time intervals, has garnered significant attention due to its broad applications in fields like fire detection, environmental monitoring, disaster assessment, urban planning, and land management. As a result, CD is a growing focus for researchers worldwide.

In the context of climate change and escalating natural disasters, accurate and timely weather forecasting is paramount. One factor that directly affects the results of this forecasting depends on the changes in clouds. Moreover, their analysis and interpretation of these images are also challenging due to the complex interplay of temporal and spatial dimensions in weather phenomena. Consequently, several strategies, including artificial neural modeling [1, 2], fuzzy computing system [3, 4], hybrid techniques [5], etc., have been used for recognizing changes in RSI. These methods can increase change forecasting's robustness and accuracy, especially in complex and uncertain contexts.

The rapid advancement of artificial intelligence has leads to increases in the extensive integration of computational intelligence models in various domains, attracting significant attention from researchers worldwide [5]. These models have proven valuable in feature extraction, classification, segmentation, and image recognition tasks. For instance, researchers have developed an automatic coding method integrated with convolutional neural networks to address challenges in concurrent noise image processing [6]. Additionally, the U-Net neural network architecture has been employed for precisely segmenting damaged skin areas, enabling removing unwanted components [7].

Determining the noteworthy alterations that have transpired across a sequence of pictures over an extended duration is crucial for change detection, as it facilitates decision-making. However, due to various factors, such as the observable phenomena, the acquisition method, and the image processing processes, images are frequently intrinsically imprecise. The complex fuzzy inference system (CFIS), which considers the inaccuracies, the unknown, and the vagueness elements of images at various phases, has been the center of attention for many academics lately. Previous research has demonstrated the efficacy of complex fuzzy logic in time-series forecasting. The Mamdani CFIS was presented by Selvachandran et al. in 2019 [8] as an effective method to deal with temporal and uncertain challenges. Lan et al. further advanced this work by proposing two improved variants of M-CFIS [9, 10].

The potential use of CFIS for picture change predictions has also received attention in recent studies. Giang et al. [11–13] proposed a spatial-temporal CFIS model for forecasting satellite cloud images and detecting changes. However, their approach has limitations, particularly in its simplified mechanisms for image blurring and deblurring, which primarily focus on individual or small groups of pixels rather than capturing broader contextual relationships. This limitation in previous work was our primary motivation for the current research. In this study, we propose an enhanced Spatial CFIS system that uses convolutional neural networks (CNNs) for the fuzzification and defuzzification procedures. By integrating CNNs, we aim to capitalize on the advantages of machine learning for feature extraction and representation, ultimately improving the accuracy and robustness of the spatiotemporal forecasting model. To confirm the model's efficacy, we performed tests to evaluate our suggested model's reliability against other established approaches in satellite image forecasting.

In the following section, we detail our novel spatial complex fuzzy inference system (CFIS) integrated with CNNs for fuzzification and defuzzification, enabling effective feature extraction and image enhancement. Subsequently, we present experimental results using a remote sensing image dataset from the US Navy and compare our model against relevant studies. The final section summarizes our findings, discusses limitations, and outlines potential avenues for future research.

II. PROPOSED NOVEL SPATIAL COMPLEX FUZZY INFERENCE SYSTEM

1. Main ideas of the proposed method

The "change detection problem" on remote sensing images refers to determining the modification of an object or an occurrence by monitoring the images at various points in time. Figure 1 describes details of the proposed Spatial CFIS-CNN that integrates the spatial CFIS with CNN to analyze and forecast RS images.

First, there is a preprocessing stage for the input image, where the input image sequence will be decomposed into three color channels corresponding to the red, green, and blue (RGB) channels. Then, each color channel will be run through 2 convolution layers and two max-pooling layers, reducing the representation to 128x128 for each color channel. This stage aims to extract the necessary information while reducing computational complexity by using max pooling to reduce the size of each image. These are the outstanding characteristic information of the original image.

Next, the model will conduct clustering and generate spatial complex fuzzy rules in a triangular fuzzy form based on the features extracted from the input image. Furthermore, during the training process, the rule set will be evaluated by considering whether the predicted image is appropriate by calculating the RMSE value of the input image and the next predicted image in the training set. If the rule set is not suitable, it will return to adjusting the kernel value of the CNN.

After obtaining a set of rules suitable for the training data set, the model calculates the output image corresponding to the input images in the testing set. The final predicted image is achieved by applying defuzzification coefficients and convolution calculations to the feature vectors representing each color channel.

2. Detailed of Novel Spatial CFIS

Step 1: Preprocessing

Step 1.1. Separate 3 RGB color channels from the input color image

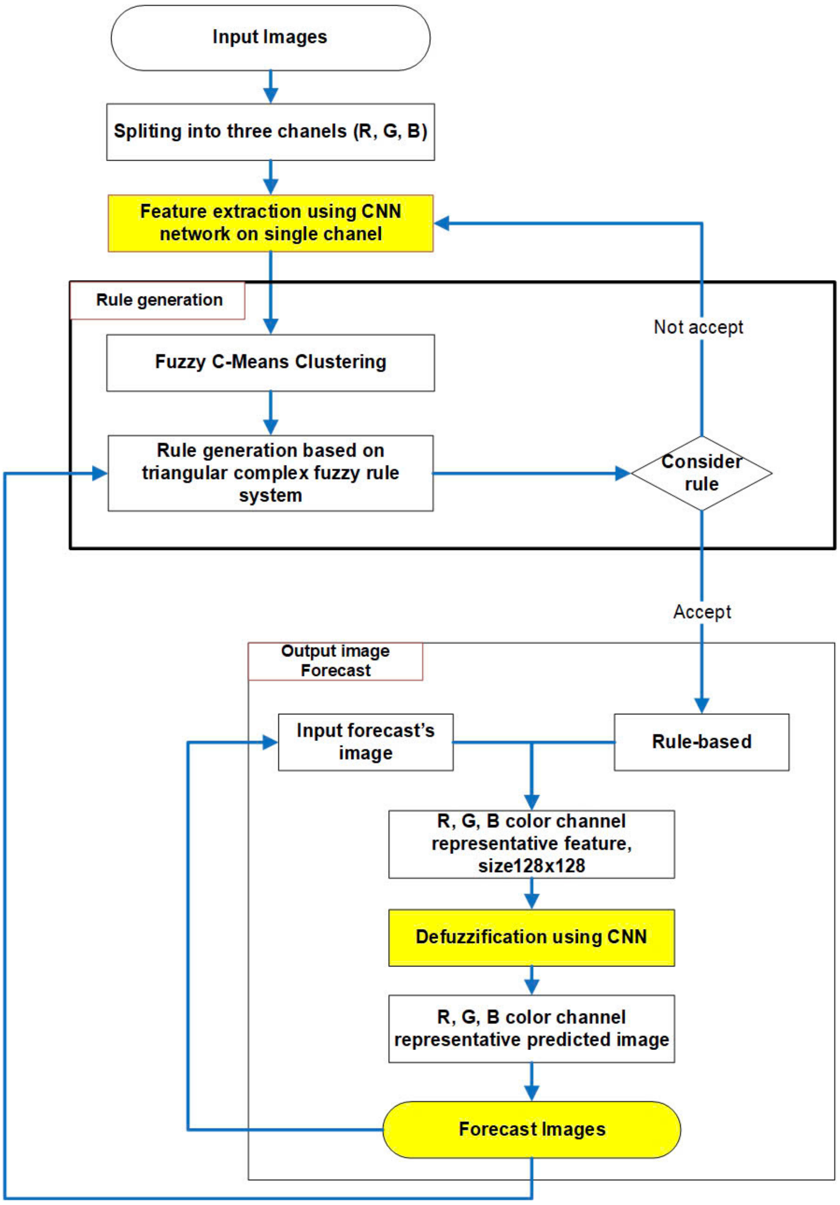

Figure 1. Overview of the Novel Spatial CFIS CNN.

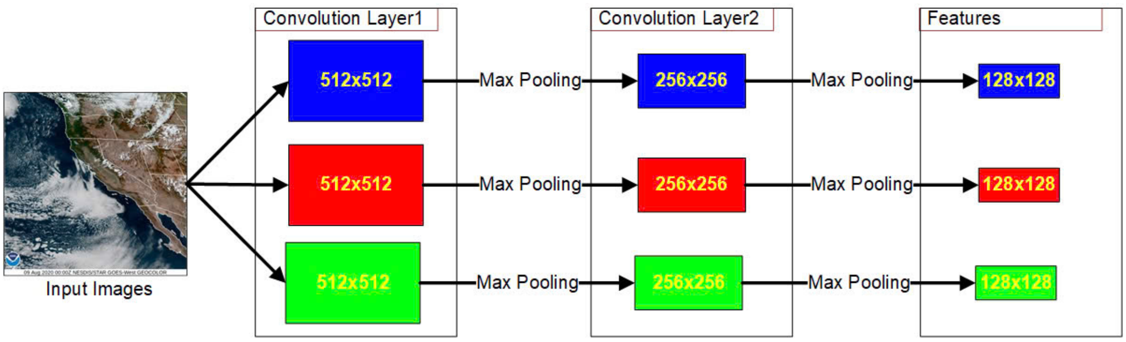

Figure 2. Feature extraction using the CNN.

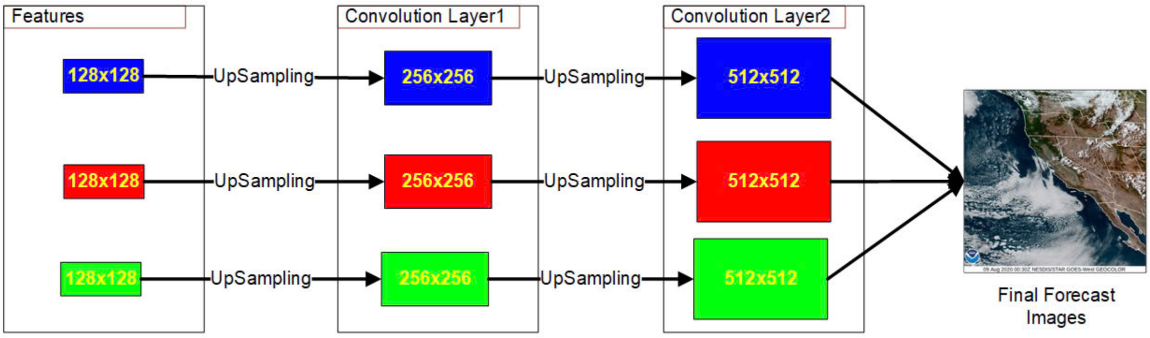

Figure 3. Defuzzification using the CNN.

Step 1.2. Feature Extraction (Per Channel)

One of the elements that impact a model's success is the input data. We found that using images directly according to each color channel, as research [12] has shown, will affect the effectiveness of the model because this input image data may contain a lot of noise. In addition, the pixels used independently can lead to problems such as overfitting, especially with limited data. So, to solve this problem, we suggest using the CNN network to solve the above issues.

This step contains four layers as follows:

- Convolutional Layer 1: Each color channel undergoes feature extraction through a convolutional layer, transforming the input data (originally 512x512 pixels) into a 512x512 feature map with stride = 1 and padding = 1, kernel-size = 3x3 and using ReLU function to ensure that the value is not overscale. This step identifies and emphasizes essential patterns within the image data.

- Max Pooling Layer 1: The feature map is downsampled using a 2x2 max pooling layer, reducing its dimensions to 256x256. This step retains the most prominent features while decreasing computational complexity.

- Convolutional Layer 2: Another convolutional layer is applied to the downsampled feature map, further refining the representation of the image data while maintaining the 256x256 dimensions with stride = 1 and padding = 1, kernel-size = 3x3 and using the ReLU function to ensure that the value is not overscale.

- Max Pooling Layer 2: A final max pooling layer (2x2) is used to obtain the final feature representation for each color channel, resulting in a compact 128x128 feature map. This map serves as a concise summary of the most relevant visual information in each color channel.

These extracted features compute a difference matrix for each color channel. This matrix is determined by calculating the phase data of each feature, representing the distinctive information within each channel. Each element in the difference matrix corresponds to a specific color channel and is calculated using Formula (1) $HoD_k(i), i = 1, .., N$, which quantifies the discrepancy between the corresponding feature regions $X^{(t)}$ across different color channels at time t and $k = 1, ..., d$.

$$HoD_k(i) = X^{(t)} - X^{(t-1)} \tag{1}$$

Step 2: Fuzzy C-Means Clustering

The feature vectors, consisting of real and phase components for each color channel, are clustered using the Fuzzy C-Means algorithm. This soft clustering technique allows each feature vector to have partial membership in multiple clusters, providing a nuanced representation of the data.

Step 3: Rule Generation

Based on the fuzzy clustering results, a set of rules is generated according to the triangular spatial complex fuzzy rule system [11]. These rules establish relationships between the feature values and the corresponding cluster memberships, capturing the underlying patterns in the data.

Step 4: Output Interpolation

Step 4.1. Feature Mapping and Scaling for Complex Fuzzy Space.

The representative features for each color channel are initially mapped into the complex fuzzy space defined by the triangular membership functions determined in Step 3. However, due to variations in preprocessed image data, some feature values may fall outside the boundaries of this defined space. To ensure all features are within the valid range for subsequent interpolation, a scaling operation is introduced.

A scaling coefficient, denoted as α, is determined. This coefficient is used to scale down any feature values that lie outside the complex triangular fuzzy space. By dividing these outlier feature values α, their positions are adjusted so that they fall within the region where membership values can be effectively calculated for the triangular fuzzy membership functions. This normalization step ensures that all features contribute meaningfully to the interpolation process.

Step 4.2. Interpolation of the output values of each color channel through the feature vector.

After synthesizing the membership function values for the representative feature vector of each color channel within the complex fuzzy space, the output value $O_i^* = \left(O_{i.\mathrm{Re}l}^*, O_{i.\mathrm{Im}g}^*\right)$ is calculated. This calculation utilizes formulas (2) and (3) to interpolate the output and progress to Step 6.

$$O_{i.\mathrm{Re}l}^* = \frac{\sum_{j=1}^{q} \min_{1\le k\le d} U_{A_{kj}}(X_i^{(k)}) * DEF(X_i)}{\sum_{j=1}^{q} \min_{1\le k\le d} U_{A_{kj}}(X_i^{(k)})} \quad (2)$$

$$O_{i.\mathrm{Im}g}^* = \frac{\sum_{j=1}^{q} \min_{1\le k\le d} U_{A_{kj}}(X_i^{(k)}) * DEF(HoD_i)}{\sum_{j=1}^{q} \min_{1\le k\le d} U_{A_{kj}}(X_i^{(k)})} \quad (3)$$

Where:

- $O_{i.\mathrm{Re}l}^*$: A vector containing the forecast feature values for each color channel
- $O_{i.\mathrm{Im}g}^*$: A vector that measures the difference between the original given image features $X_i^{(k)}$ and the forecasted image features.
- $U_{A_{kj}}(X_i^{(k)})$: The degree of membership of a specific feature vector $X_i^{(k)}$ to the j-th fuzzy rule.
- $DEF\ (X_i)$: the defuzzification coefficient parameters for the real part of features $U_{A_{kj}}(X_i^{(k)})$ based on the j^{th}.
- $DEF\ (HoD_i)$: The defuzzification coefficient for a feature's phase (or imaginary) part is also calculated according to the j^{th} fuzzy rule.

$$DEF(X_i) = \frac{h_1 a + h_2 b + h_3 c}{\sum_{i=1}^{3} h_i} \quad (4)$$

$$DEF(HoD_i) = \frac{h'_1 a' + h'_2 b' + h'_3 c'}{\sum_{i=1}^{3} h'_i} \quad (5)$$

Step 5: Defuzzification Weight Training

The defuzzification weights, represented by $DEF\ (X_i)$ and $DEF\ (HoD_i)$ for the real and phase parts, respectively, are trained in this step. This training process aims to optimize the weights so that the defuzzified output values accurately reflect the desired image characteristics.

The defuzzification function, which utilizes the trained weights, is calculated according to formulas 4 and 5. These formulas consider the fuzzy membership values, the rule antecedents, and the defuzzification coefficients to generate the final crisp output values for each pixel in the image.

To achieve high-quality image forecasting, it is crucial to determine suitable optimal defuzzification weights $(h_1,\ h_2,\ h_3,\ h_1',\ h_2',\ h_3')$. The Adam optimization algorithm Adam [14] is employed for this purpose, leveraging its adaptive learning rate and momentum-based updates to efficiently converge towards the optimal weight values and minimize the root mean square error (RMSE) value:

$$RMSE = \sqrt{\sum_{i=1}^{n} \left(X_i^{(t)} - \hat{X}_i^{(t)}\right)^2} \quad (6)$$

$\hat{X}_i^{(t)}$ is the feature vector of the forecast value of each color channel and is determined by Formulas 2 and 3.

Step 6. Output Image Forecasting

Step 6.1: Forecast Output Features for Each Color Channel

The forecast feature values for the next image in each color channel, denoted as O_i^*, are calculated by combining the forecastings for the real $O_{i.\mathrm{Re}l}^*$ and imaginary (phase) components $O_{i.\mathrm{Im}g}^{*'}$. The forecasting is performed according to Formula 7 as follows:

$$O_i^* = \alpha \times O_{i.\mathrm{Re}l}^* + (1-\alpha) \times O_{i.\mathrm{Im}g}^{*'} \quad (7)$$

Where:

- $O_{i.\mathrm{Re}l}^*$: The forecast feature value is based on the real part of the image data. - $O_{i.\mathrm{Im}g}^{*'}$: The feature value forecast based on the rate of change in the phase component of the image - $\alpha \in\ [0,1]$: The dependency coefficient modulates the contribution of the phase forecasting to the overall output. To optimize the forecasting accuracy, the Adam optimization algorithm is employed to determine the most suitable value for the dependency coefficient α. The goal is to minimize the root mean square error (RMSE) within the forecast image and the real image.

Step 6.2. Final Image Synthesis and Upsampling

After obtaining the forecast feature vectors for each color channel (as described in Step 6.1), these vectors are synthesized into a full-resolution image. This involves a multi-step process that upsamples the feature representations and combines them into a single image.

- Upsampling to 256x256: The feature vectors, initially sized 128x128, are upsampled to a resolution of 256x256 using a suitable interpolation technique. This can be done using methods like bilinear interpolation or transposed convolutions.

- Feature Transformation: A convolutional layer is applied to the upsampled features to transform them into a 256x256 representation suitable for further upsampling. This layer reverses the feature extraction process earlier in the pipeline.

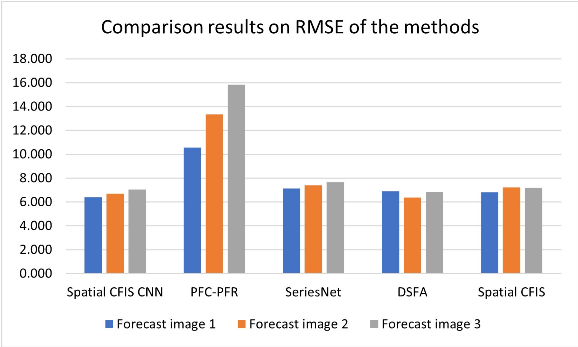

Figure 4. Comparison results of RMSE for Image Forecasting Models.

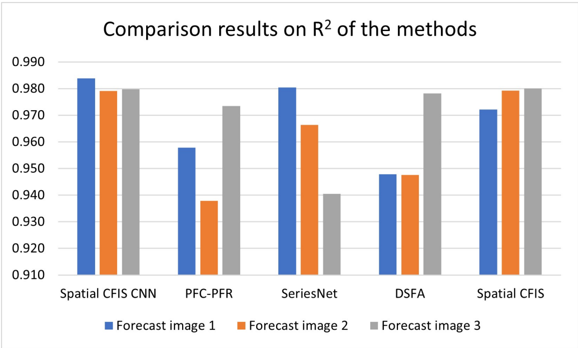

Figure 5. Comparison results of R^2 for Image Forecasting Models.

-Final Upsampling: The 256x256 feature maps are further upsampled to the original image size of 512x512. This step ensures that the forecast features align with the spatial dimensions of the original input image.

- Channel Combination: The final forecast image is created by combining the red, green, and blue feature maps that have been upsampled. This is typically done by concatenating the channels along the depth dimension.

- Output: The synthesized 512x512 image represents the final dehazed forecasting, as illustrated in Figure 3. This image is the culmination of the entire pipeline, incorporating the extracted features, fuzzy rules, and optimized defuzzification weights.

III. EXPERIMENT RESULTS

Dataset: The experimental data consists of consecutive satellite images captured at 30-minute intervals over the Gulf of Mexico region. Sourced from the US Navy's weather image database [12], the dataset comprises three sets, each containing ten images with a resolution of 512x512 pixels. For each set, the last three images are designated as forecasting targets, while the remaining images are used for training. These data, after preprocessing, will be used as input for the CNN model.

Experimental environment: The algorithm is implemented using Python and executed on a Macbook Pro M1 with chip M1 Pro, 16GB RAM, and 512GB SSD hard drive.

The evaluation metrics: We compared the recommended Spatial CFIS CNN model and other well-known techniques for predicting changes in remote sensing pictures to evaluate its performance. These methods incorporate various factors, including fuzzy and spatial and temporal elements. The following algorithms represent them: SeriesNet[15], Picture fuzzy clustering algorithm (PFC-PFR) [16], deep slow feature analysis DSFA [17] and Spatial CFIS [11].

The comparison was based on two evaluation metrics: Root Mean Square Error (RMSE) and Corrected R-squared Coefficient (R^2). The RMSE index compares the deviation of the predicted image with the actual image, which is determined through the value of each pixel at each corresponding position of the predicted image and the actual image. (R^2) index plays a role in evaluating the model's reliability. Specifically, the average outcomes of 10 experimental runs are used to get the final (R^2) result.

Experiment Results and discussion:

The comparison findings between the other models on the two corresponding indicators, RMSE and (R^2), are shown in the figures 4 and 5. Figure 4 illustrates the comparative performance of the our suggested model and other related models in terms of Root Mean Square Error (RMSE). The results demonstrate a notable improvement in accuracy for the proposed model, particularly in the forecasting of the first forecast image, where it outperforms PFC-PFR, SeriesNet, DSFA, and Spatial methods by 39.32%, 10.17%, 6.89%, and 5.75% respectively. This enhancement is partly attributed to the novel integration of CNN networks for image fuzzication and defuzzication within the proposed model.

Furthermore, while all models exhibited some degree of cumulative error between consecutive images, the proposed model demonstrated a significant reduction in this accumulation. The capacity of the suggested solution to capture temporal dependencies and minimize error propagation is proved by its persistent greater results in terms of explained variance over the other techniques, as demonstrated by the R2 comparison shown in Figure (R^2).

IV. CONCLUSION

This study demonstrates the effectiveness of incorporating Convolutional Neural Networks (CNNs) into a spatial complex fuzzy inference system (CFIS) for forecasting satellite cloud imagery. The proposed Spatial CFIS CNN model outperforms four established methods (PFC-PFR, SeriesNet, DSFA, and Spatial CFIS) across both RMSE and R2 metrics, indicating superior forecasting accuracy and a better fit to the data. The use of CNNs in the fuzzification and defuzzification stages appears to contribute significantly to this improvement.

However, as with any complex model, there are limitations to consider. While the proposed model reduces cumulative error compared to previous methods, it still exhibits this issue to some extent. Additionally, the computational complexity introduced by the CNN-based fuzzy operations can increase processing times. Future research directions include investigating techniques to further mitigate cumulative error and optimize the model's computational efficiency. Despite these drawbacks, the study's findings demonstrate the potential for improving time-series image data forecasting, particularly in meteorological applications, by fusing deep learning and complex fuzzy inference.

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