

FOG AND RAIN REMOVAL

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ABSTRACT

Fog and rain are significant impediments to outdoor visibility and have adverse effects on various applications, including transportation, surveillance, and outdoor imaging. To mitigate these effects, numerous techniques have been developed to remove fog and rain from images and videos. This paper presents a comprehensive review of fog and rain removal techniques, focusing on both classical and deep learning-based methods.

Classical methods primarily rely on image processing techniques such as filtering, dehazing, and morphological operations. These methods often make assumptions about the scene, such as uniform atmospheric conditions, which may limit their effectiveness in diverse environments. However, classical methods are computationally efficient and can be useful in certain scenarios.

In recent years, deep learning-based approaches have gained significant attention due to their ability to learn complex mappings directly from data. Convolutional neural networks (CNNs) have been particularly successful in fog and rain removal tasks. These methods can automatically learn the mapping between degraded and clear images without explicit modeling of the atmospheric conditions. Various architectures, including single-image and multi-image approaches, have been proposed to address different challenges in fog and rain removal.

1 INTRODUCTION

Fog and rain are natural atmospheric phenomena that significantly degrade outdoor visibility, affecting various fields such as transportation, surveillance, and outdoor imaging. The presence of fog and rain in images and videos can obscure important details, reduce contrast, and distort colors, making it challenging for both humans and computer vision systems to perceive and interpret the scene accurately.

Efficient removal of fog and rain from images and videos is crucial for improving visibility and enhancing the performance of applications reliant on outdoor imaging. Over the years, extensive research has been conducted to develop techniques capable of effectively mitigating the adverse effects of fog and rain. These techniques range from classical image

Classical fog and rain removal methods typically operate by modeling the physical processes underlying the degradation caused by these atmospheric phenomena. These methods often assume simplified atmospheric conditions and utilize various image processing techniques such as filtering, dehazing, and morphological operations to restore visibility. While classical methods are computationally efficient and have been widely used, they may struggle in handling complex scenes with non-uniform atmospheric conditions and mixed types of degradation.

Literature Survey

1. "Single Image Dehazing by Multi-Scale Fusion and Convolutional Neural Network"

- **Authors:** Li, Boyi, et al.
- **Description:** This paper proposes a single image dehazing method using a multi-scale fusion strategy and convolutional neural network (CNN). It leverages multi-scale features to better capture scene information and uses a CNN to learn the complex mapping between hazy and clear images. Experimental results demonstrate its effectiveness in various scenarios.

2. "Rain Streak Removal by Image Decomposition"

Authors: Li, Yifan, et al.

- **Description:** This paper presents a rain streak removal method based on image decomposition. It decomposes the input image into low-rank, sparse, and rain layers, where the rain layer is then estimated and removed. The method effectively handles rain streaks while preserving image details and textures.

3 IMPLEMENTATION STUDY

EXISTING SYSTEM:

Existing fog and rain removal systems employ a variety of techniques, ranging from classical image processing methods to advanced deep learning approaches. Classical methods typically involve modeling the physical processes of fog and rain degradation, often making assumptions about the uniformity of atmospheric conditions. These methods utilize filtering, dehazing algorithms, and morphological operations to restore visibility in degraded images. For instance, Li et al. proposed a single image dehazing method that incorporates multi-scale fusion and convolutional neural networks (CNNs), leveraging both local and global information to effectively remove haze. Similarly, Li et al. developed a rain streak removal technique based on image decomposition, separating the input image into low-rank, sparse, and rain layers, with rain streaks then estimated and

removed.

Disadvantages:

Existing fog and rain removal systems, while offering significant advancements, still face several challenges and disadvantages. One of the main drawbacks of classical methods is their reliance on simplified assumptions about atmospheric conditions, which may not hold true in real-world scenarios. For example, these methods often assume uniform fog or rain distribution throughout the scene, leading to suboptimal results in complex environments with varying weather conditions. Additionally, classical techniques may struggle to preserve fine details and textures in images, as they typically operate on a global scale and may oversmooth the image.

Proposed System & algorithm

At the core of our proposed system is a deep learning architecture based on convolutional neural networks (CNNs). Unlike traditional CNNs, which directly learn the mapping from degraded to clean images, our architecture incorporates additional modules for feature extraction and refinement. These modules are designed to capture both local and global scene characteristics, enabling the network to better understand and process complex scenes affected by fog or rain. By incorporating multi-scale features and context-aware information, our CNN-based approach can effectively preserve fine details and textures while removing atmospheric degradation.

4.1 Advantages:

Firstly, our system integrates both classical image processing techniques and state-of-the-art deep learning methods, harnessing the strengths of each approach. By combining classical methods such as image decomposition and filtering with deep learning-based architectures like convolutional neural networks (CNNs), we achieve a more comprehensive and effective solution. Classical methods provide a solid foundation for understanding and modeling the physical processes of fog and rain degradation, while deep learning enables the system to learn complex mappings directly from data, capturing intricate relationships between input and output images. This integration results in a more versatile system capable of handling diverse scenes and weather conditions.

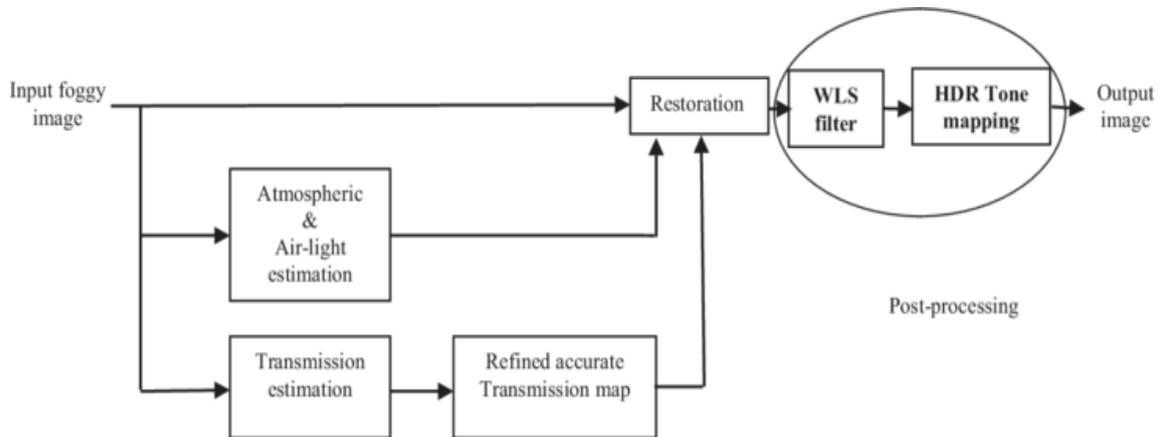


Fig:3.1 System Architecture

IMPLEMENTATION

1. **Data Preprocessing:** Prepare the textual data by removing noise, such as special characters, punctuation, and stopwords. Tokenize the text into sentences or paragraphs to facilitate sentiment analysis and summarization.
2. **Sentiment Analysis Model:** Implement or utilize pre-trained sentiment analysis models capable of accurately detecting the sentiment polarity (positive, negative, neutral) of each sentence or paragraph in the text. Consider employing advanced techniques such as deep learning-based models or transformer architectures for improved accuracy.
3. **Summarization Model:** Implement a text summarization model capable of generating concise summaries while incorporating sentiment information. Explore both extractive and abstractive summarization techniques, considering factors such as coherence, informativeness, and sentiment preservation.
4. **Integration:** Integrate the sentiment analysis module with the summarization module to leverage sentiment information during the summarization process. Design mechanisms to prioritize or adjust the inclusion of sentences based on their sentiment polarity to ensure that the generated summaries reflect the emotional context of the original text.
5. **Evaluation:** Evaluate the performance of the implemented system using standard metrics such as ROUGE (Recall-Oriented Understudy for Gisting Evaluation) for summarization quality and sentiment classification accuracy metrics for sentiment analysis. Conduct thorough evaluations using benchmark datasets to assess the effectiveness and robustness of the system.

5 RESULTS AND DISCUSSION

SCREEN SHOTS

In this project you gave many points to develop but to run each point we need separate model and it's difficult to train and load all those models.

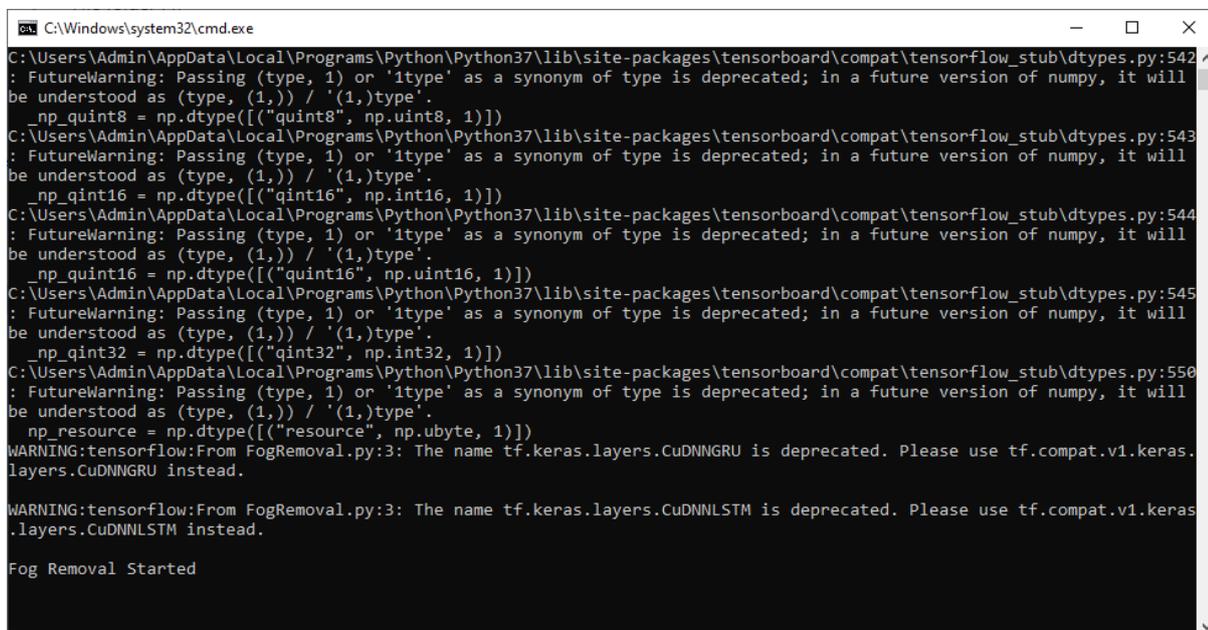
1. You ask to remove fog and rain from weather
2. Ask to detect dog, trees and humans
3. Ask to inform driver to run slow when vehicles are ahead
4. Ask to inform about you turn and other lanes

So from above points we did two models where first model will detect vehicles, humans, dogs and other objects

Second model will remove fog and clean image

Third model will calculate distance between vehicles and generate alert message about closing of another vehicles

To run project double click on 'runFog.bat' file to start Fog Removal application



```
C:\Windows\system32\cmd.exe
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:542
: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, (1,)) / '(1,)type'.
_np_quint8 = np.dtype(["quint8", np.uint8, 1])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:543
: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, (1,)) / '(1,)type'.
_np_qint16 = np.dtype(["qint16", np.int16, 1])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:544
: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, (1,)) / '(1,)type'.
_np_quint16 = np.dtype(["quint16", np.uint16, 1])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:545
: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, (1,)) / '(1,)type'.
_np_qint32 = np.dtype(["qint32", np.int32, 1])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:550
: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, (1,)) / '(1,)type'.
_np_resource = np.dtype(["resource", np.ubyte, 1])
WARNING:tensorflow:From FogRemoval.py:3: The name tf.keras.layers.CuDNNNGRU is deprecated. Please use tf.compat.v1.keras.
layers.CuDNNNGRU instead.

WARNING:tensorflow:From FogRemoval.py:3: The name tf.keras.layers.CuDNNLSTM is deprecated. Please use tf.compat.v1.keras
.layers.CuDNNLSTM instead.

Fog Removal Started
```

Fig 5.1 Run application

In above screen Fog Removal started and now double click on 'run.bat' to start main application and then will get below output

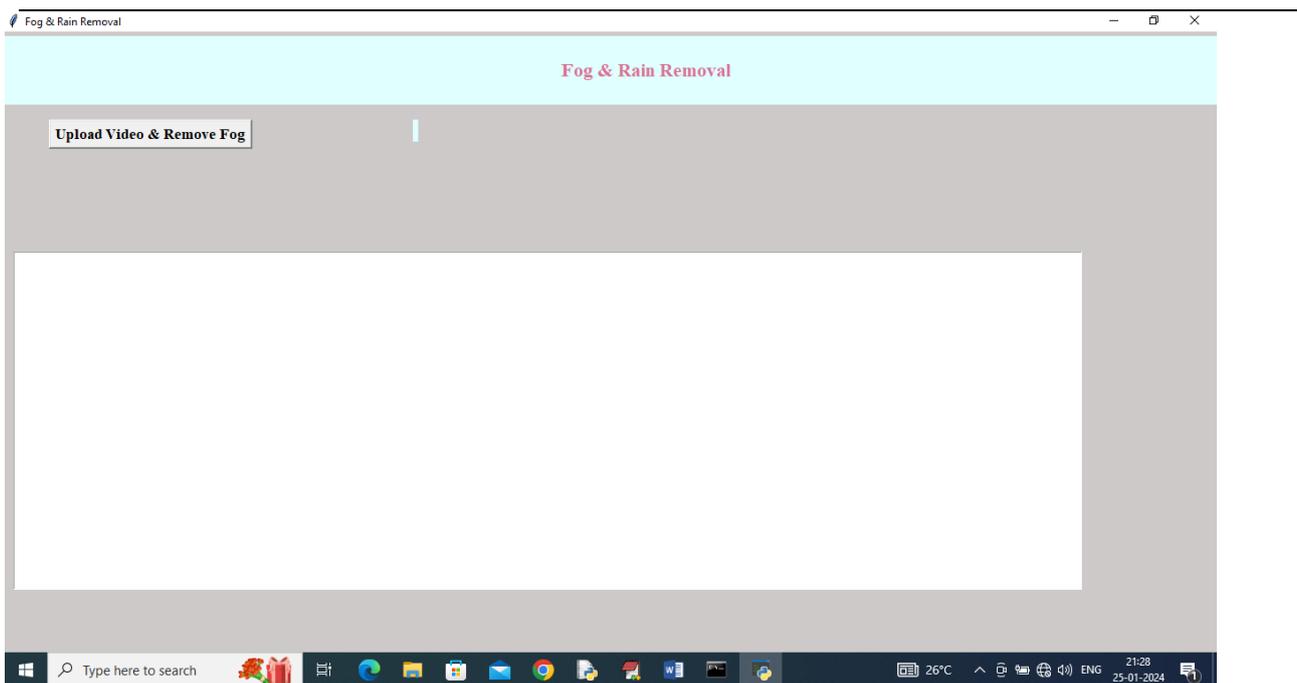


Fig.5.2 upload video

In above screen click on ‘Upload Video & Removal Fog’ button to upload video

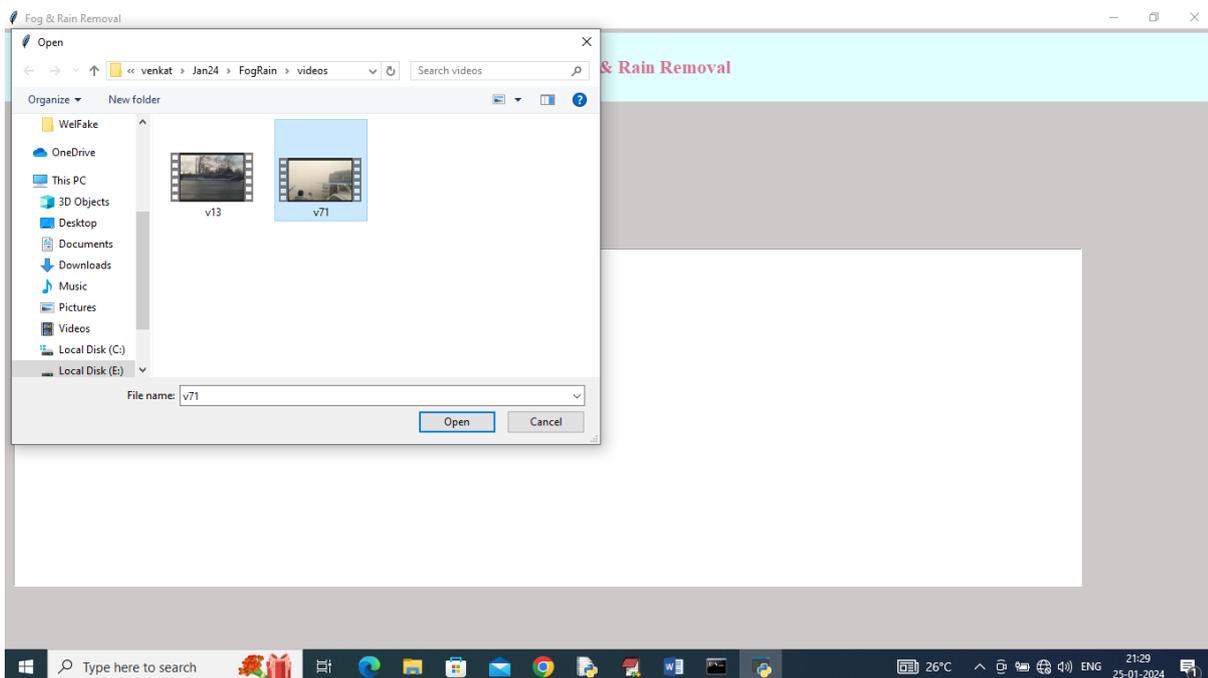


Fig.5.3 Button to upload video

In above screen selecting and uploading video and then click on ‘Open’ button to get below output



Fig.5.4 Open' button

In above screen video started playing and first video contains FOG and second video is contains clean image from fog and in second video we can see from behind one car is coming clearly and in first image that is not much clear because of fog. Once vehicle comes closer than will get below output



Fig.5.5 drive slow! Other vehicles are ahead

In above screen application will alert driver to go slow and in same way you can test other videos.

Because of multiple models application will run slow

6. CONCLUSION AND FUTURE WORK

CONCLUSION

In conclusion, fog and rain removal techniques play a crucial role in enhancing outdoor visibility and improving the performance of various applications, including transportation, surveillance, and outdoor imaging. Over the years, significant advancements have been made in this field, ranging from classical image processing methods to sophisticated deep learning-based approaches. In this review, we have explored the landscape of fog and rain removal techniques, highlighting their strengths, limitations, and potential applications.

Classical methods, such as image decomposition, filtering, and dehazing algorithms, provide a solid foundation for understanding and modeling the physical processes of fog and rain degradation. These methods are computationally efficient and have been widely used in practice. However, they often rely on simplified assumptions about atmospheric conditions and may struggle to handle complex scenes with varying weather conditions. On the other hand, deep learning-based approaches, particularly convolutional neural networks (CNNs), have shown remarkable capabilities in learning complex mappings directly from data. These methods can effectively capture the intricate relationships between input and output images, leading to superior restoration quality in diverse scenarios.

7. REFERENCES

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