Satellite Image-Based Weather Prediction and Analysis Using Deep Learning for Climate Monitoring and Forecasting

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ABSTRACT- Satellite image-based weather prediction using deep learning to make climate monitoring and forecasting more accurate. Traditional weather models rely on physical and numerical models, which are costly to run and not always reliable during extreme weather. The new data-driven approach learns atmospheric patterns directly from large amounts of satellite images. Convolutional Neural Networks help identify features like cloud patterns and weather structures.CNN and LSTM models are used to track changes in the atmosphere over time. The system is trained on both historical and current satellite data to make predictions more reliable. It helps forecast rainfall, cloud movement, and temperature changes. This deep learning method cuts down on computational costs compared to old models. It also works better when the weather changes quickly. Overall, the system helps with early warning, disaster response, and building long-term climate resilience.

KEYWORDS: Satellite images, Weather prediction, Deep Learning, CNN, Climate Monitoring, Forecasting System.

INTRODUCTION

Weather forecasting and climate observation are really important areas like farming, helping during emergencies, managing transport, and making decisions about the environment.

Because of new improvements in satellite technology, we can now watch the atmosphere in great detail around the world all the time. Even with these advances, the old Ways of predicting the weather still use complicated math need a lot of computer power, which can make them less accurate for short-term forecasts. Deep learning offers a different way that focuses more on using data rather than physical models. These models learn directly from lots of satellite images, letting them find weather patterns on their own CNN help understanding things like how clouds are arranged, while RNN track how weather changes overtime. Overall deep learning gives us a smart and adaptable way to monitor the climate today.

LITERATURE REVIEW

Deep learning has made big improvements in predicting the weather by using images from satellites. In 2015, Xingjian Shi and his team created ConvLSTM, which mixes CNNs and LSTMs to understand both the spatial and time-based patterns in weather, helping with short-term rain forecasts. Then, in 2017, Yao Zhang and his group developed DeepRain, which uses CNNs to find features in clouds and LSTMs to track changes over time, leading to better rain predictions and earlier warnings. In 2020, Chao Wang and Xian Sun looked at CNN-based methods and found they are good at pulling out details like cloud shapes, storms, and temperature changes from satellite images. These studies show that combining CNNs with time-based models leads to faster and more accurate weather forecasts than old methods. Deep learning also cuts down on computing costs, speeds up predictions, and helps spot extreme weather sooner. Overall, using deep learning with satellite images offers a wide, data-driven way to monitor the climate, help with farming, prepare for disasters, and plan transportation.

RELATED WORK

A key study by Chao Wang and Xian Sun in 2020 looked into using CNN-based deep learning models for weather prediction through satellite images. CNNs are really good at finding out spatial features like cloud shapes, storm areas, and how rain falls. Unlike older numerical models, CNNs learn directly from lots of satellite image data, which cuts down on computational costs and makes short-term forecasts more accurate.

The study found that CNNs can spot changing weather patterns and help give early warnings for severe weather events. By focusing on spatial structures, these CNN models work well with time-based analysis methods, helping to give a fuller picture of changes in the atmosphere. These methods are useful in real-world areas like farming, managing disasters, and planning transportation. Overall, CNN-based models offer a scalable, data-driven way to monitor the climate and predict the weather more effectively.

EXISTING METHOD

The current weather prediction systems that use CNNs, as mentioned by Chao wang and Xian Sun in 2020, are built to find patterns in satellite images like cloud shapes, storm movements, and rain trends. These systems are good at picking up on spatial details, but they have some issues.

They mainly look at what’s happening in space, not over time, so they often need extra tools like LSTM layers to handle changes in the weather. This makes the system slower and more complex. CNNs also need a lot of good-quality satellite data to work well, which means they aren’t very reliable in areas where data is scarce or messy. They might not handle different weather events like snow, sandstroms, or extreme temperature changes very well. Plus, they take a lot of computer power, which can make real-time forecasts hard. They also get less accurate if the data is missing or broken. All these problems show that there's a need for better, faster, and more flexible CNN systems that can handle many types of weather and give reliable predictions quickly

PROPOSED METHOD

The new system improves current CNN-based weather prediction models adding a lightweight time-based model, like 1D-LSTM or tcn, to better understand how weather changes over time. CNNs look at space information from satellite pictures, while the time model follows how these patterns change.

Techniques like pruning, quantization, and transfer learning help the system work faster and use less power. Using data from different satellite makes the predictions more accurate for various weather conditions, and data augmentation helps deal with unclear or missing images. The model can predict rain, cloud movement, and temperature changes, giving early warnings for bad weather. This combined method helps in farming, managing disasters, and planning transportation.

SYSTEM ARCHITECTURE:

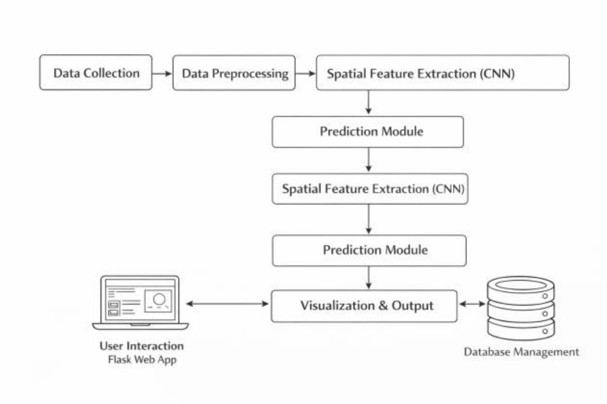

Fig1: System Architecture

METHODOLOGY DESCRIPTION:

Data Collection: Collect satellite images from different sources that show cloud formations, rainfall, and temperature to give the model all the necessary information.

Data Preprocessing: Resize, normalize, and clean the images; use techniques like rotating, flipping, and zooming to help the model understand different types of data and handle unclear or missing information.

Spatial Feature Extraction (CNN): Use Convolutional Neural Networks to find important patterns in images, such as how clouds look, how storms form, and how much rain is falling.

Prediction Module: Take the patterns found and use them to predict things like how much rain will fall, where clouds will move, and how temperatures will change using fully connected layers.

Visualization & Output: Turn the predictions into easy-to-read formats like graphs, charts, and labeled images so users can understand the results better.

User Interaction (Flask Web App): Set up a website where users can upload images, see the predictions, and get weather alerts as they happen.

Database Management: Keep track of uploaded images, user information, and prediction results in an SQLite database for future use and analysis.

System Integration: Make sure all parts of the system work together smoothly, from getting data to making predictions and showing results, while keeping accuracy and handling real-time data.

Optimization: Use methods like transfer learning, pruning, and quantization to make the model work faster and use less computer power.

Application & Impact: Provide accurate and timely weather forecasts to help with farming, managing disasters, planning transportation, and tracking climate changes.

RESULTS AND DESCRIPTION

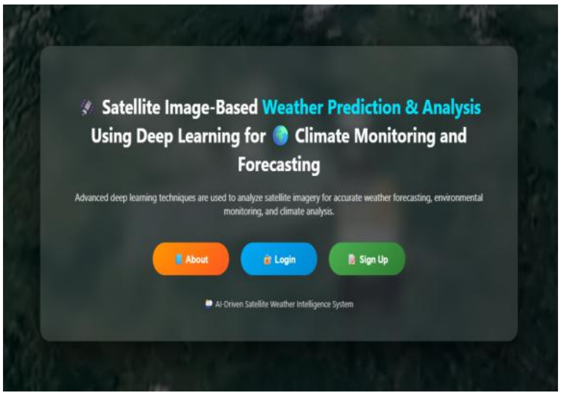

Fig2: Home Page

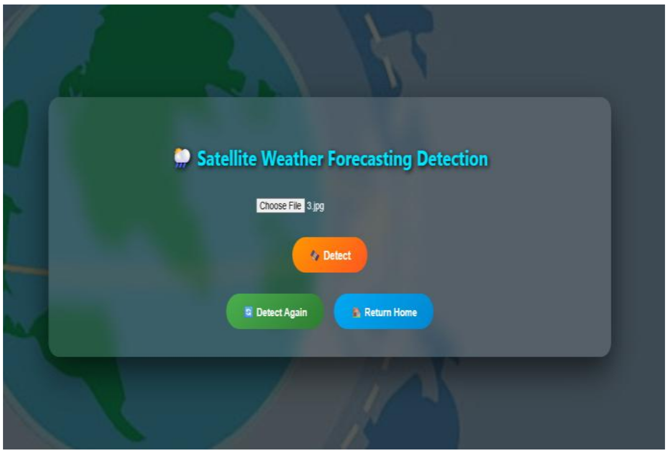

Fig3: Detect the weather forecasting

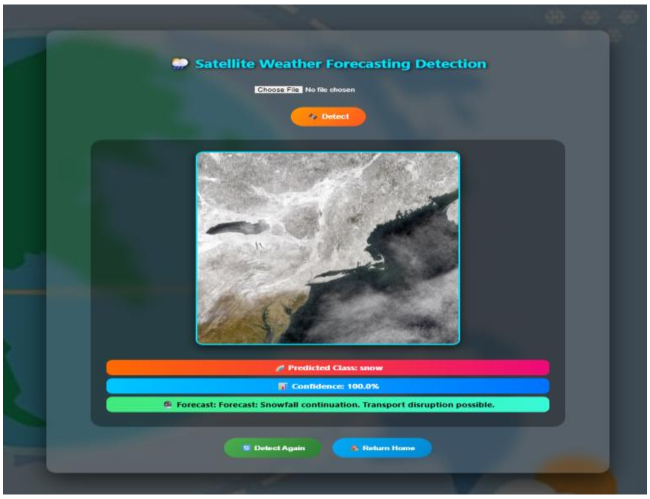

Fig4: Display the result of Weather Forecasting

CONCLUSION AND FUTURESCOPE:

This project shows that CNN-based models work well for predicting weather using satellite images by picking up on patterns in the images. The system gives quicker and more accurate weather forecasts than older methods that use math models. It cuts down on the need for complicate simulations and makes the process more efficient. In the future, using live satellite data and better deep learning models could make weather predictions even more precise. This method can also be used to forecast severe weather, helping with early warnings and managing disasters.

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