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Forest protection and development with weather forecast by Artificial Intelligence

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Abstract: *Vietnam is a country located on the Pacific coast, bordering the East Sea, with a coastline of 3,260 km, not including the islands. Vietnam's coastal forest area is very large and is focused on development for the defense and economic purposes. Due to the impact of climate change, in recent years, Vietnam has been affected by storms with more frequency and strength. To protect and coastal forests, Vietnam also has the advanced satellite and monitoring system to monitor and warn of natural disasters early to avoid damage [1]. However, the traditional technologies require a lot of computing resources to be able to accurately forecast from several weeks to several months in advance. With the increasingly unpredictable climate, we need the technology that can process big data at a faster speed, helping to make decisions faster. This paper introduces a CNN+LSTM artificial intelligence model with less computation time. This is a model with a hierarchy called Nowcasting for fast prediction within a few hours. The model can predict fast-changing phenomena such as thunderstorms, tornadoes, and hail.*

Keywords:* *forest protection, Nowcast, LSTM, weather forecasting, marine weather forecast

I. INTRODUCTION

Due to its unique geographical location along the sea, Vietnam is blessed with a rich coastal forest ecosystem. Vietnam also focuses on developing this ecosystem by planting more casuarinas along the mangrove areas. Mangrove forests play an important role in preventing coastal erosion, preventing high tides, and protecting the mainland during storms. Mangrove forests provide food and diverse habitats for many types of organisms. Currently, Vietnam is the world leader in mangrove forest area with a total mangrove forest area of about 200,000 hectares. To protect this resource, weather forecasting research is necessary because it helps in good forest care.

In the current context, we clearly see that climate change is increasingly severe and unpredictable. The world has experienced many types of extreme weather such as storms, thunderstorms, tornadoes, flash floods, droughts, heat waves, and hail. These phenomena tend to increase in frequency and intensity, especially with sudden changes in path, trajectory, and strength. According to the United Nations Office for Disaster Reduction, over the past 20 years, natural disasters have increased in frequency, affecting 4 billion people and killing 1 million people. Economic losses are also not small, with the figure of 3,000 billion USD [1].

Fig. 1. Mangrove forests in Ca Mau Cape - Vietnam [24]

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Fig. 2. A corner of naturally regenerated forest in Xuan Thuy National Park - Vietnam [24]

Vietnam has a long coastline, so it is also a country affected by extreme weather. Every year, it receives about 10 storms and tropical depressions in the East Sea. With an advanced monitoring system, Vietnam has monitored and warned many large storms in the East Sea [1][6][7][8]. The research on the weather in the sea is an important field that always needs to be upgraded and improved technology. In that context, we introduce a weather forecasting model using AI. The model is used to quickly warn in a short time within a few hours to avoid storms and tornadoes. This model is suitable for quickly processing local data for important sea areas with concentrated forests, and where radar stations are installed to collect a lot of data.

For AI models, input data is very important. It is used to train, evaluate and help infer the right results. In the next section, we will study about the monitoring devices and data sources that serve for marine weather forecasting.

II. MONITORING EQUIPMENT AND DATA SOURCES

To forecast the weather at sea, we need many different data sources. Each source has its own characteristics and plays a different role.

1. Coastal radars [9][14]

Meteorological radar can be installed on land or on ships. It operates on the principle of transmitting microwaves into space and receiving signals reflected back from target objects such as clouds and related weather phenomena. The strength or weakness of the received radio echo signal depends on the effective reflection area and the physical properties, shape and density of the cloud particles [14].

Fig. 3. Coastal radar [14]

Radar collects all radio frequency response signal values within its scanning radius from 100m to several kilo-meters. Each weather phenomenon such as rain, thunderstorms, hail... usually has a different structure, physical properties, and particle density distribution, corresponding to each type of weather phenomenon. When the radar observes, it will collect certain radio frequency response signal value thresholds for each phenomenon. Building radio frequency response signal value thresholds corresponding to each type of weather phenomenon is decisive in accurately determining weather phenomena. Here are some examples of radar indicators: [15]

For the rain forecast index causing reduced visibility <=5km:

- Cmax (Composite Maximum Reflectivity): >= 40 dBZ

- Hmax (Height of Maximum Reflectivity): >= 1,5 km

- Etop (Echo Top Height): >= 4 km

- CAPPI (Constant Altitude Plan Position Indicator) 3km: >=32 dBZ

The correlation equation between actual rainfall Y and radar-estimated rainfall X are constructed as follow: [14]

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Y = 0.4812*X + 0.9348, with the correlation coefficient = 0,6.

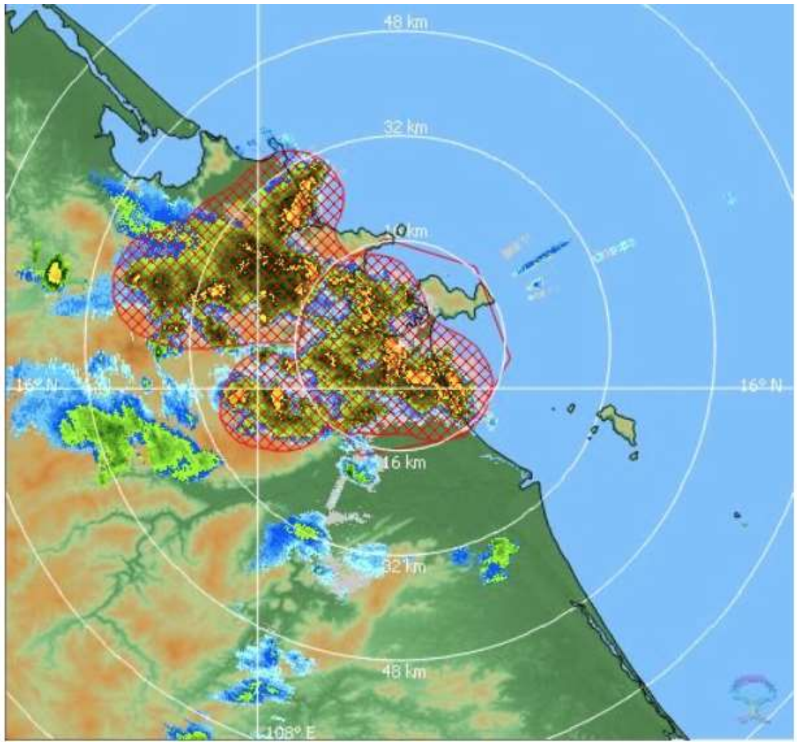

Fig. 4. Radar reports thunderstorms in the red area [15]

2. Geostationary satellites [10][16][17][18]

Satellites provide data from image channels including visual spectrum (VIS), near infrared (NIR) and infrared (IR). Through satellite images, we can observe a large area of the formation and development of convective clouds that cause rain. Currently, the Himawari satellite can provides good images of the weather situation in the world. The Himawari satellite has 16 channels with parameters of albedo and brightness temperature with high temporal resolution. The areas were scanned every 10 minutes and the spatial resolution was 2 km. The spatial resolution was 0.020 x 0.020 pixels cropped and filtered for the Vietnam study area. In addition, Altimetry is another satellite altimeter, using satellite radar to measure Sea Surface Height (SSH), indirectly estimating Ocean Heat Content (OHC) and currents.

Fig. 5. Image of the Earth from Himawari satellite [17]

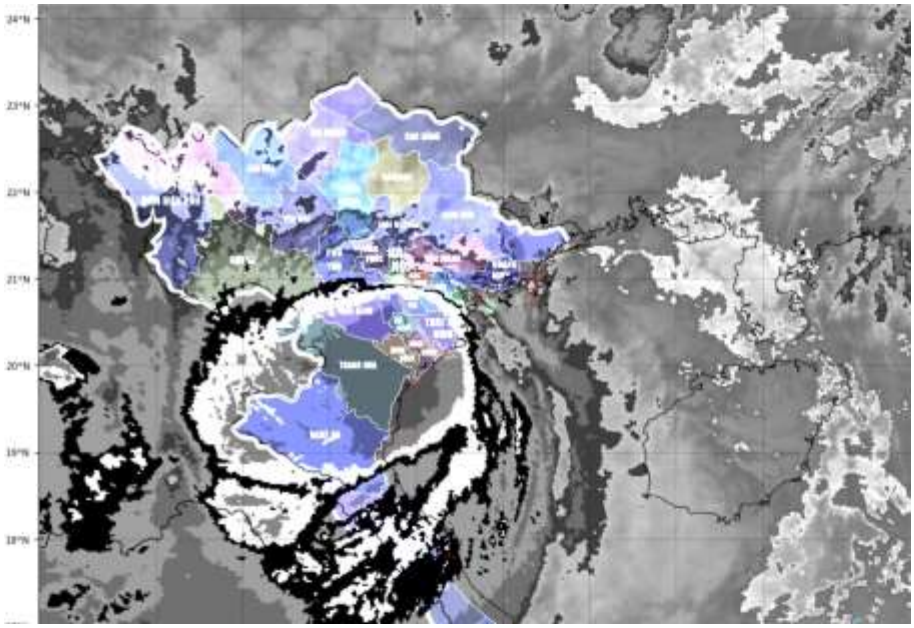

Fig. 6. Image of northern Vietnam in July 2025 from Himawari satellite [20]

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3. Types of buoys [19]

In addition to satellites, there are also buoys such as Moored buoys (fixed mooring buoys) that are fixed at a location at sea, continuously measuring sea surface temperature (SST), wind, waves, and currents. Wave buoys are used to measure wave height, period, and direction, extremely important in the East Sea, where storms are frequent. Argo floats are free-floating buoys that can dive to a depth of 2000m and then resurface to transmit data. Argo provides vertical profiles of temperature and salinity (T/S profiles).

4. Global reanalysis

Global reanalysis is the standard data for training AI models. For example, the ERA5 global climate-weather reanalysis dataset is considered the "gold standard" for AI research and training. The key features of ERA5:

- Spatial resolution uses grid spacing ~0.25° × 0.25° and covers the globe.
- Time resolution is 1 hour/time (hourly data). Includes data from 1950 to present.
- Data is integrated from satellites, radars, meteorological stations, buoys, aircraft, radiosondes. More than 200 variables, including temperature, humidity, wind (u, v, w), pressure, rain, solar radiation, snow, clouds, surface data (SST, land), 3D fields by pressure levels.

In the field of weather forecasting, Numerical Weather Prediction (NWP) is a traditional weather forecasting technique by solving physical equations describing the motion of the atmosphere and ocean (Navier–Stokes, thermodynamic equation, humidity equation). This method has been used for many decades, can predict from 15 to 30 days. However, they require a lot of computational resources (requires supercomputers). The resolution is limited, usually 9–25 km. It is difficult to capture local phenomena such as thunderstorms and rapidly developing storms.

Currently, AI models for weather forecasting calculate quickly. They reduce the decision time. To promote the strengths of each architecture, ERA5 can be used as training/validation data, then test on real forecast data from Numerical Weather Prediction (ECMWF/GFS). This helps ensure that the model learns from "truth" (reanalysis) and verifies on "reality" (operational forecast). In the next section, we will study the model for fast weather forecasting within a few hours. In the next section, we will learn in depth about the AI model called CNN + LSTM.

III. FAST FORECASTING MODEL

This is the pipeline of the process from data collection to the final step of producing weather forecast results.

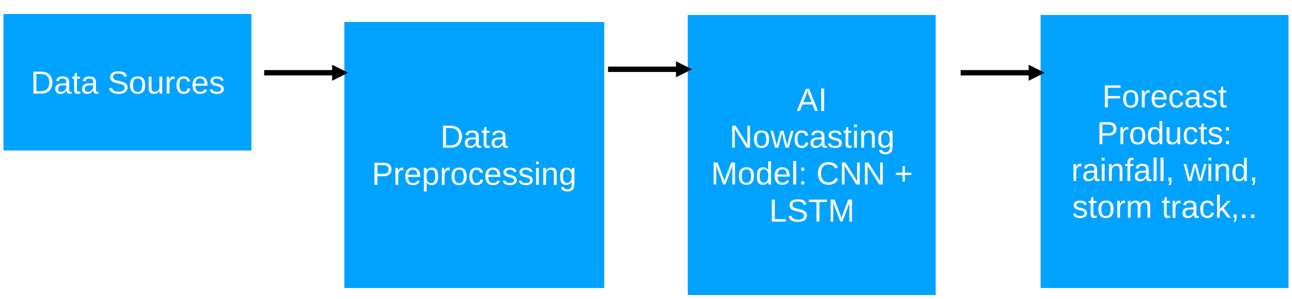

Fig. 7. Pipeline of weather forecast by AI

3.1 Data Preprocessing

For all radar sources, satellites, IoT/wave buoys, Argo, altimetry, NWP, the data is typically processed in the following steps before being used to train an AI model:

1. Check for redundancy, data loss, missing data, and data duplication
2. Cleaning
3. Interpolation / regridding
4. Time alignment
5. Normalisation / scaling
6. Chunked storage

3.2. Architecture of LSTM [26]

The basic structure in LSTM revolves around three main gates: Forget Gate, Input Gate and Output Gate, along with a special memory that helps the model process long data sequences efficiently.

- Forget Gate: The forget gate decides which information from the previous state should be retained or discarded. It uses a sigmoid activation function to generate a value between 0 and 1, where 0 means discarding the old information completely and 1 means keeping the information. This mechanism allows the LSTM to filter out unnecessary information, optimizing the ability to remember important data.

- Input Gate: The input gate determines which information from the new input should be added to the memory. This mechanism consists of two main steps: a sigmoid function (deciding which parts of the information should be updated) and a tanh function (generating a candidate vector containing the new data), which is then combined with the output of the sigmoid function to adjust the memory. This allows the LSTM to selectively incorporate new information, helping the model adapt to the data over time.

- Output Gate: The output gate controls what information will be passed to the next step. The mechanism of operation includes: sigmoid function (filtering important information from memory) and tanh function (adjusting the memory state before giving the result). The output gate helps LSTM focus on important features and limit noise, increasing the accuracy of the model in sequence processing problems

LSTM consists of a series of memory cells, which operate sequentially according to the following mechanism:

1. Remove unnecessary information at the Forget Gate.
2. Add new information to the memory at the Input Gate.
3. Output important information at the Output Gate.

The output gate determines which part of the information will be passed to the next step. The process works as follows: First, use the sigmoid function to determine the influence of the memory state. Then use the tanh function to adjust the memory value before outputting.

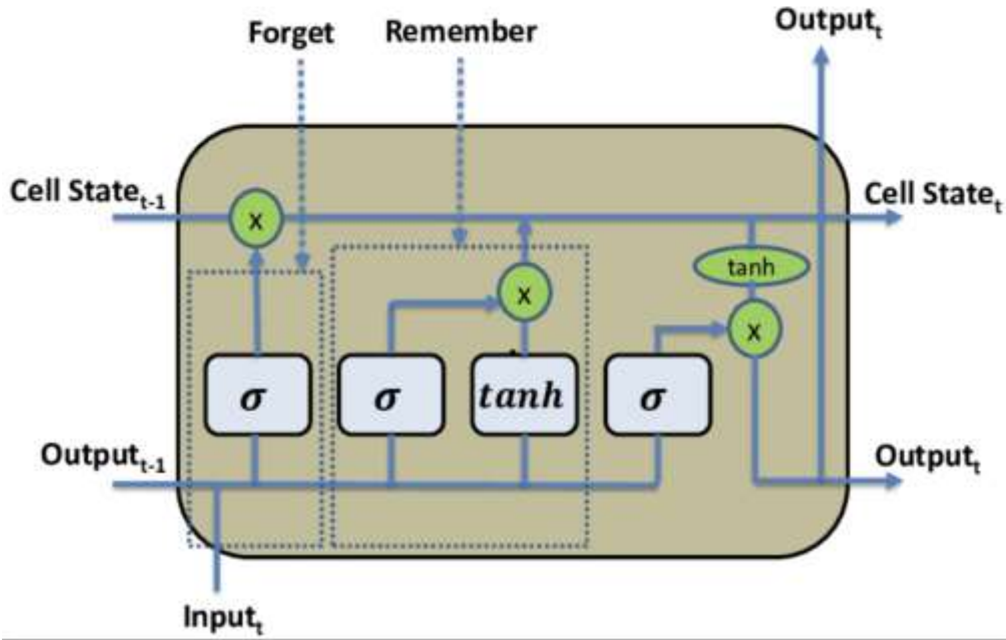

Fig. 8. The basic structure in LSTM revolves around three main gates [26]

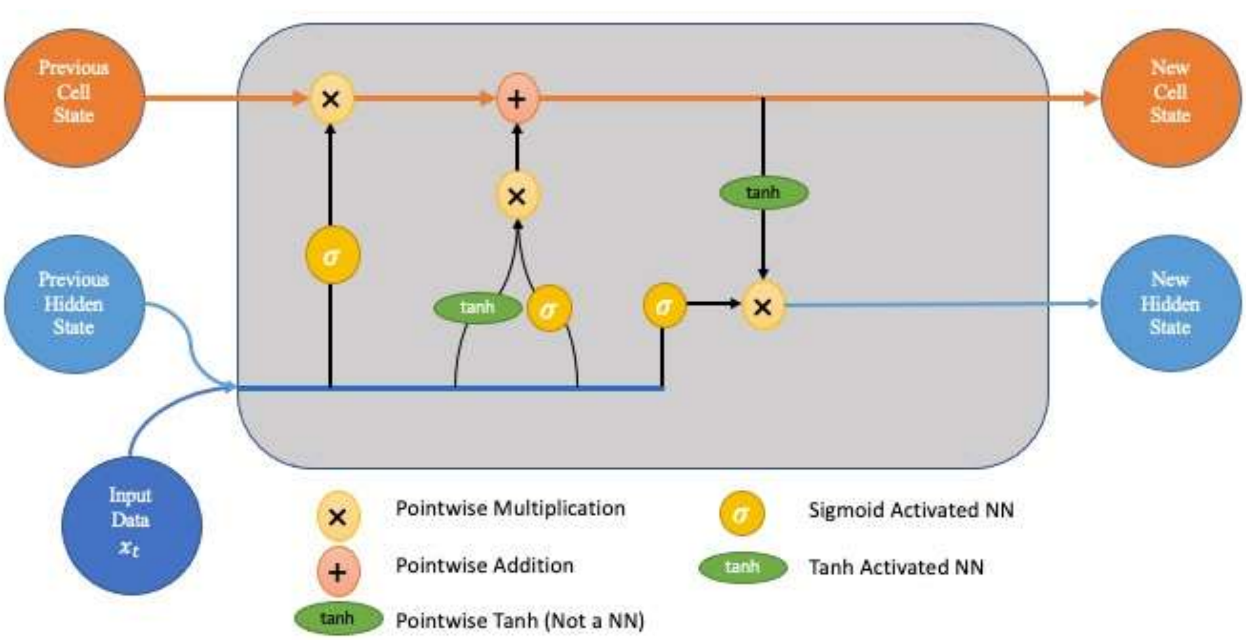

Fig. 9. The LSTM model consists of a chain of memory cells containing three main gates [26]

3.3. Using LSTM for rainfall regression [28][29]

- Formula of LSTM Core:

$$(h_t, c_t) = \mathrm{LSTM}(x_t, h_{t-1}, c_{t-1})$$

Where:
x_t: input vector at time t (radar image, satellite, IoT buoy, NWP features).

h_t: hidden state (short-term memory, containing information from the most recent time).

$\mathbf{c}_t$: cell state (long-term memory, retains information longer).

- Formula of rainfall regression:

$$\hat{R}(t+1) = W_r \cdot h_t + b_r$$

Where: W_r, b_r are the learned weight matrix and bias.

3.4. Using LSTM and CNN to predict the storm center coordinates [30][31][32]

LSTM is specialized for processing temporal data. To process satellite images with spatial characteristics, we need to combine CNN model. CNN extracts spatial features from cloud images. Then LSTM learns the shifting trend through time series. Finally, Fully Connected layer regresses to the storm center coordinates.

- **Step 1**: Feature extraction from satellite cloud images.

$$f_t = \mathrm{CNN}(I_t), \quad f_t \in \mathbb{R}^d$$

Where:
. I_t: Satellite image at time t (patch around storm).

. f_t: Feature vectors extracted by CNN.

- **Step 2**: Time series modeling with LSTM to learn hurricane development and migration dynamics.

$$(h_T, c_T) = \mathrm{LSTM}([f_{t-k}, f_{t-k+1}, \ldots, f_t])$$

Where: h_T is the hidden state and $\mathbf{c}_T$ is the cell state.

- **Step 3**: Forecast of storm center coordinates

$$(\hat{Lat}, \hat{Lon})_{t+1} = W_s \cdot h_T + b_s$$

Where:
. (Lat^, Lon^): forecast latitude and longitude of the storm center.

. Ws, bs : learned parameters.

3.5. Example of code

This is a code in Pytorch used to build a model combining CNN and LSTM. The model can be trained on satellite image series (satellite patches) and forecast the center of the storm coordinates (lat - Latitude, lon - Longitude)

```
# ---------------- CNN Encoder + LSTM Model ————————————

class CNNEncoder(nn.Module):
    def __init__(self, in_ch=1, feat_dim=128):
        super().__init__()
        self.net = nn.Sequential(
            nn.Conv2d(in_ch, 16, 3, padding=1), nn.BatchNorm2d(16), nn.ReLU(),
            nn.MaxPool2d(2),
            nn.Conv2d(16, 32, 3, padding=1), nn.BatchNorm2d(32), nn.ReLU(),
            nn.MaxPool2d(2),
            nn.Conv2d(32, 64, 3, padding=1), nn.BatchNorm2d(64), nn.ReLU(),
            nn.AdaptiveAvgPool2d((1,1)),
        )
        self.fc = nn.Linear(64, feat_dim)
    def forward(self, x):
        f = self.net(x).view(x.size(0), -1)
        return self.fc(f)

class CNNTowerLSTM(nn.Module):
    def __init__(self, in_ch=1, feat_dim=128, hidden_dim=128, num_layers=1, T_in=6):
        super().__init__()
        self.encoder = CNNEncoder(in_ch=in_ch, feat_dim=feat_dim)
        self.lstm = nn.LSTM(feat_dim, hidden_dim, num_layers, batch_first=True)
        self.fc = nn.Sequential(
            nn.Linear(hidden_dim, hidden_dim//2),
            nn.ReLU(),
            nn.Linear(hidden_dim//2, 2)  # predict (y,x)
        )
    def forward(self, seq):
        B, T, C, H, W = seq.shape
        encoded = []
        for t in range(T):
            f = self.encoder(seq[:,t])
            encoded.append(f)
        enc_seq = torch.stack(encoded, dim=1)  # (B, T, feat_dim)
        out, (hn, cn) = self.lstm(enc_seq)
        h_last = out[:, -1, :]
        return self.fc(h_last)
```

IV. CONCLUSION

The article has just introduced data sources and models for short-term marine weather forecasting to cope with increasingly unusual and highly variable weather phenomena. This technology, when applied, will bring high efficiency to the work of conserving and developing mangrove forests, which are a valuable resource of the earth. In the future, this model will continue to be studied to assess the environment under different conditions and with different sets of indicators such as assessing radiation, wave height, flow direction variation, etc.

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