Project Report
Weather Classification Using Deep Learning

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1. INTRODUCTION

1.1 Project Overview

Categorizing weather conditions is vital for meteorologists and forecasters to anticipate and convey upcoming weather patterns. Recognizing various weather phenomena significantly impacts our day-to-day routines. Assessing these phenomena plays a pivotal role across multiple areas such as environmental monitoring, weather prediction, and evaluating environmental standards. Furthermore, distinct weather occurrences have varying impacts on agriculture, making precise identification crucial for enhancing agricultural strategies.

1.2 Purpose

The objectives are as follows:

- Allow user interaction with the UI to select an image.
- Process the chosen image through a VGG19 deep learning model.
- Integrate the VGG19 model into a Flask application.
- Utilize the VGG19 model to analyze the image and produce predictions.
- Display these predictions on the Flask UI for user review.
- Enable users to swiftly input an image and receive accurate predictions.

To achieve this, the following tasks need completion:

- Data Collection:
  - Download and extract the dataset.
- Image Pre-processing:
  - Import necessary libraries.
  - Set up the ImageDataGenerator class.
  - Apply ImageDataGenerator functionality to the Trainset and Testset.
- Model Building:
  - Use a pre-trained CNN model as a Feature Extractor.
  - Add Dense Layer.
  - Configure the Learning Process.
  - Train the model.
  - Evaluate Model Accuracy.
  - Save the Model.
  - Test the model.
- Application Building:
  - Create HTML Pages.
  - Develop Flask Code.
  - Launch the Application.

2. Literature Survey

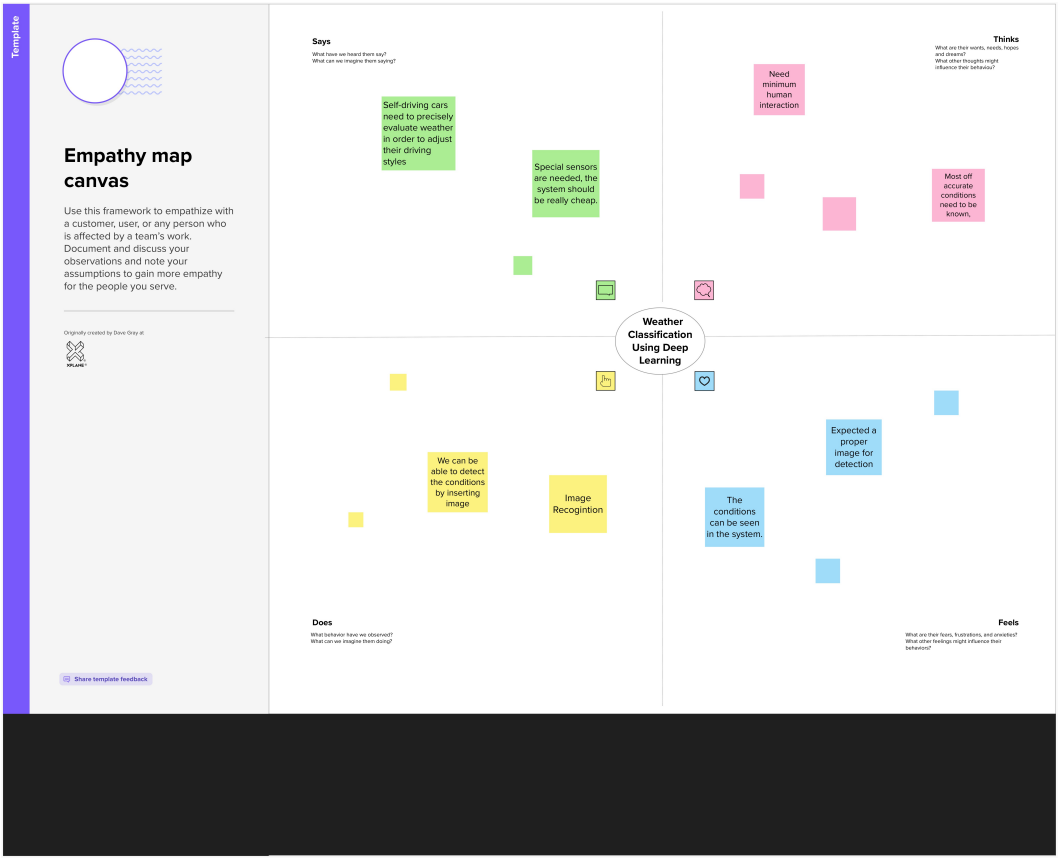
2.1 Existing Problem

2.2 Problem Statement Definition

Identifying weather patterns is a widespread challenge across various industries. Contemporary agriculture heavily relies on analyzing present meteorological situations. A potential solution involves a weather detection system using images, eliminating the necessity for specialized sensors, thereby ensuring a cost-effective system.

3. Ideation & Proposed Solution

3.1 Empathy Map Canvas



3.2 Ideation & Brainstorming

Step 1: Team Gathering and Problem Statement Selection

Problem Statement:

Weather classification is vital for agriculture, transportation, and disaster management. Accurate classification aids crop yield optimization, efficient route planning, and better preparedness for extreme weather events.

Challenges:

Conventional methods lack generalization across regions and seasons, leading to inaccuracies in unique or data-scarce areas.

Proposed Solution:

Develop an automated weather classification system using transfer learning from pre-trained deep learning models, like ImageNet, to enhance accuracy and robustness.

Specific Challenges:

1. Dataset Collection: Gather diverse, labelled weather images covering various conditions.
2. Model Selection: Identify and fine-tune pre-trained models for weather classification.
3. Generalization: Ensure the model performs well across different locations and seasons.

Additional Considerations:

- Use data augmentation and cross-validation techniques.
- Explore explainability methods for model understanding and bias identification.

Step 2: Brainstorming and Grouped Ideas

1. Dataset Collection:
   - Collect diverse labeled weather images from multiple sources.
   - Preprocess images for noise removal and standardization.
2. Model Architecture and Transfer Learning:
   - Evaluate pre-trained models like VGG or ResNet for weather classification.
   - Adapt and fine-tune models for optimal performance.
3. Spatial and Temporal Context:
   - Utilize multi-scale convolutional filters for varied weather patterns.
   - Develop temporal models considering weather changes over time.
4. Domain Adaptation and Generalization:
   - Transfer knowledge across regions for improved adaptability.
   - Incorporate external data sources to enhance generalization.
5. Evaluation and Performance Metrics:
   - Define suitable metrics and address class imbalance issues.
   - Estimate uncertainty for prediction reliability.
6. Real-time Deployment and Optimization:
   - Design efficient pipelines for real-time classification.
   - Optimize models for resource-constrained devices.

7. Visualization and Interpretability:
    - Develop visualizations for model feature understanding.
    - Create user-friendly interfaces for presenting results.

These strategies outline the development path for an effective weather classification system using transfer learning.

4. Requirement Analysis

4.1 Functional Requirement

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement	Sub Requirement
FR – 1	User Registration	Registration through Form Registration, through Gmail Registration, through LinkedIN
FR – 2	User Confirmation	Confirmation via Email Confirmation via OTP
FR – 3	User Interface	It allows users to capture images of garbage and see the results of the classification in real-time.
FR – 4	AI Model	The project should use an AI algorithm that can learn from data and improve over time.
FR – 5	Real Time Classification	It should be able to classify images quickly and accurately as soon as they are captured by a camera.

4.2 Non-Functional Requirement

Following are the non-functional requirements of the proposed solution.

NFR No.	Non- Functional Requirement	Description
NFR – 1	Performance	Performance forecasting is an essential service to support decision-taking in the concept, design and operational phases of an asset, meeting the production efficiency challenge by enhancing operational performance
NFR – 2	Reliability	A seven-day forecast can accurately predict the weather about 80 percent of the time
NFR – 3	Security	Stay indoors and move to a shelter.
NFR – 4	Scalability	Global efforts to bring about crucial improvements in supercomputing efficiency and energy usage were placed center stage this week as the European Centre for Medium-Range Weather Forecasts (ECMWF) welcomed users and vendors from

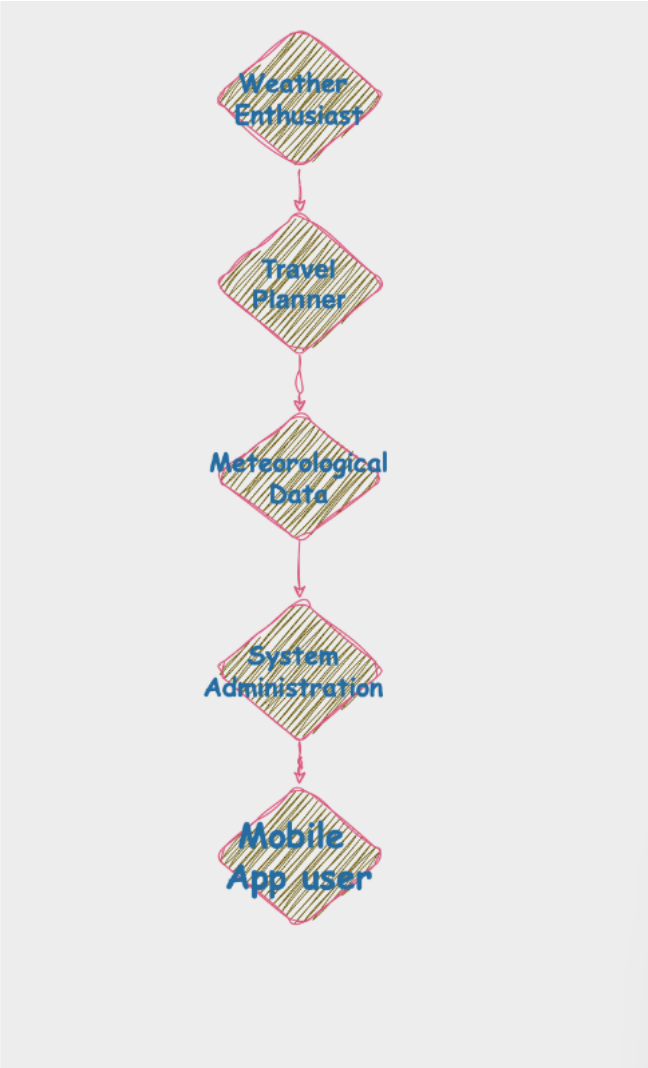
		around the world to London for the Cray
NFR – 5	Usability	Weather Forecasting is crucial since it helps to determine future climate changes.

5. Project Design

5.1 Data Flow Diagrams & User Stories

Data Flow Diagrams:

A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system. A neat and clear DFD can depict the right amount of the system requirement graphically. It shows how data enters and leaves the system, what changes the information, and where data is stored.



User Stories:

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance Criteria	Priority	Release
Weather Enthusiast	Real-time Weather Classification	1	Receive Current Weather Information	- Real-time weather data for the user's location	High	Sprint-1
Weather Enthusiast	Real-time Weather Classification	2	View Weather Trends Over Time	- Historical weather trends displayed with graphs	Medium	Sprint-2
Travel Planner	Historical Weather Data	3	Access Historical Weather Reports	- Access to historical weather data for chosen destinations	High	Sprint-2
Meteorological Data	Data Upload and Model Training	4	Upload New Weather Data for Analysis	- Secure upload process with confirmation of ingestion	High	Sprint-1
System Administrato	Model Performance Monitoring	5	Monitor Deep Learning Model Performance	- Metrics, charts, and alerts for model performance	High	Sprint-1
System Administrato	Model Performance Monitoring	6	Ensure Data Security and Privacy Compliance	- Regular security audits and compliance with regulations	High	Sprint-1
Mobile App User	User Interface and Notifications	7	Receive Push Notifications for Severe Weather	- Push notifications for severe weather conditions	High	Sprint-1
Mobile App User	User Interface and Notifications	8	User-Friendly Interface for Weather Exploration	- Intuitive interface for exploring current and historical weather	Medium	Sprint-2

5.2 Solution Architecture

Solution architecture is a complex process – with many sub-processes – that bridges the gap between business problems and technology solutions. Its goals are to:

- Find the best tech solution to solve existing business problems.
- Describe the structure, characteristics, behavior, and other aspects of the software to project stakeholders.
- Define features, development phases, and solution requirements.
- Provide specifications according to which the solution is defined, managed and delivered

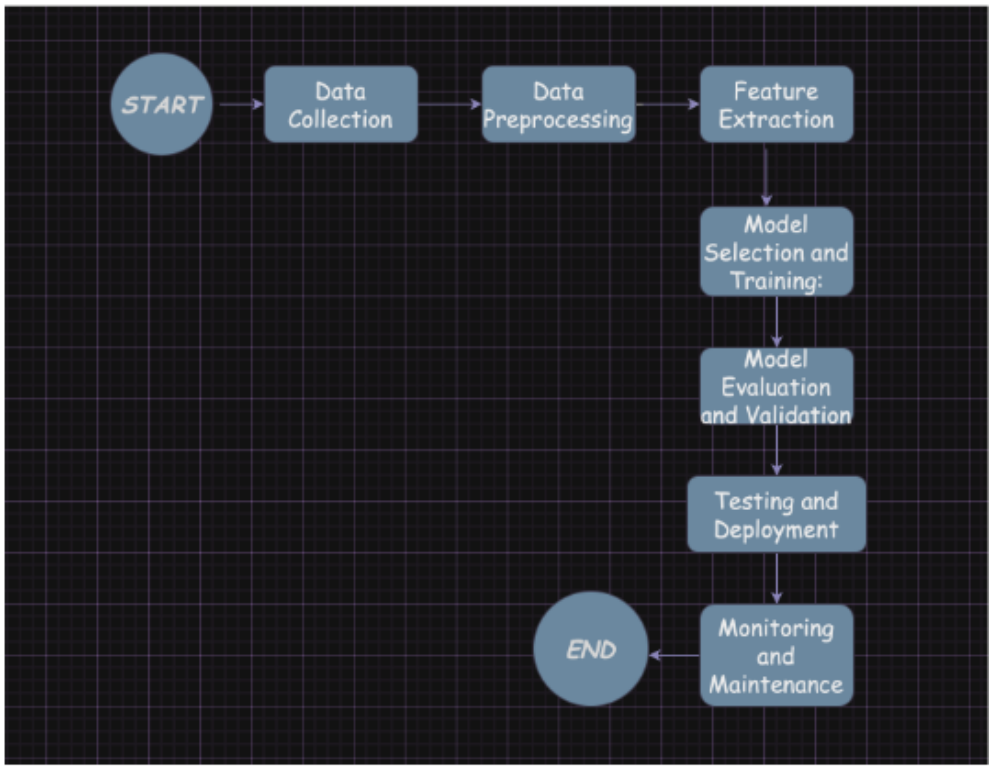


Figure 1: Architecture and data flow of the voice patient diary sample application

6. Project Planning & Scheduling

6.1 Technical Architecture

Table-1: Tech Stack

SNo.	Component	Technology/Service Used
1.	User Interface	Tkinter (Python GUI toolkit)
2.	Application Logic-1	TensorFlow (Python)
3.	Application Logic-2	IBM Watson Speech to Text (STT) service
4.	Application Logic-3	IBM Watson Assistant
5.	Cloud Database	IBM Cloudant (Assumed based on Watson services)
6.	Machine Learning Model	VGG19 model (pre-trained)
7.	Infrastructure (Server / Cloud)	Local Server Configuration: N/A (Code not designed for local server) Cloud ServerConfiguration: IBM Cloud Foundry or Kubernetes (assumed based on IBM Watsonservices)

Table-2: Application Characteristics

SNo.	Characteristics	Description	Technology
1.	Open-SourceFrameworks	TensorFlow (open-source machine learning framework)	TensorFlow
2.	Scalable Architecture	Limited scalability due to the frozen VGG19 architecture	VGG19 (pre-trained and frozen layers)
3.	Availability	Dataset availability is crucial for training and evaluation	N/A (Dependent on dataset availability)
4.	Performance	Data augmentation, GPU utilization, and batch size considerations	TensorFlow (Data augmentation, GPUsupport, batch processing)

6.2 Sprint Delivery Schedule

Sprint	Phase	Tasks	Start Date	End Date
1.	Project Initiation Phase	Define Project Goals and Objectives	August 1, 2023	August 7, 2023
		Assessment of Scope and Requirements		
		Identify Key Stakeholders and Expectations		
2.	Data Collection and Preparation	Data Collection	August 8, 2023	August 29, 2023
		Model-specific Data Requirements		
		Ethical Considerations		
3.	Team Formation and Resource Allocation	Assemble the Project Team and Assign Responsibilities	August 30, 2023	September 6, 2023
		Identify Necessary Resources, Including Hardware, Software, and External Tools/APIs		
4.	Task Breakdown and Timeline Planning	Task Breakdown	September 7, 2023	September 13, 2023
		Detailed Timeline		
		Set Milestones		
5.	Model Selection and Architecture Design	Research and Model Selection	September 14, 2023	September 28, 2023
		Architecture Design		
6.	Data Pre-processing Plan	Data Pre-processing Steps	September 29, 2023	October 6, 2023
		Address Potential Challenges		
7.	Training and Evaluation Strategy	Dataset Splitting and Training Strategy	October 7, 2023	October 21, 2023
		Hyperparameter Tuning and Model Training		
		Evaluation Metrics and Criteria		
8.	User Interface Design and Real-time Integration	UI Design	October 22, 2023	November 5, 2023
		Real-time Integration		
		Features and Functionalities		
9.	Documentation and Reporting Structure	Code Documentation	November 6, 2023	November 13, 2023
		Project Report		
		Metrics and KPIs		
10.	Testing and Deployment Plan	Testing Strategy	November 14, 2023	November 28, 2023
		Deployment Plan		
		Configuration Considerations		
11.	Continuous Improvement and Iteration	Regular Reviews and Iterations	November 29, 2023	Ongoing

7. Coding & Solutioning

```
from flask import Flask, render_template, request, url_for
import os
from flask import flash,redirect
from werkzeug.utils import secure_filename
import os
import shutil
from PIL import Image
from tensorflow import keras
from keras.layers import Dense
from keras.models import Sequential, load_model
from tensorflow.keras.preprocessing import image
import numpy as np

def predict_model(img):
    model =  load_model('weathermodel.h5')
    x = image.img_to_array(img)
    x = np.expand_dims(x,axis = 0)
    preds = model.predict(x)
    pred = np.argmax(preds,axis = 1)
    index = ['cloudy','foggy','rainy','sunshine','sunrise']
    result = str(index[pred[0]])
    return(result)

def resize_image(image_path, width, height):

    with Image.open(image_path) as img:
        resized_img = img.resize((width, height))
        resized_img.save(image_path)

app = Flask(__name__)
app.secret_key = 'supersecretkey'

@app.route('/')
@app.route('/index.html')
def index():
    return render_template('index.html')
@app.route('/about.html')
def about():
    return render_template('about.html')
@app.route('/pictures.html')
def pictures():
    return render_template('pictures.html')
@app.route('/upload.html')
def up():
    return render_template('upload.html')
```

```
@app.route('/upload', methods=['POST'])
def upload():
    file = request.files['file']
    filename = secure_filename(file.filename)
    print(filename)
    file.save(os.path.join(app.config['UPLOAD_FOLDER'], filename))
    path = 'static/{}'.format(filename)
    resize_image(path,300,300)
    img = image.load_img(path,target_size = (180,180))
    result = predict_model(img)
    return render_template('res.html', image_url=url_for('static',
filename=filename),result = result)

if __name__ == '__main__':
    app.config['UPLOAD_FOLDER'] = 'static'
    app.run(debug=True)
```

8. Performance Testing

8.1 Performance Metrics

1. Precision, Recall, Accuracy, F1
   These metrics are widely used in binary classification where only two categories are taken into consideration. In multi classification solutions they might be calculated in multiple ways, but the most popular is to calculate them as the average of every single metric across all classes. Precision represents proportion of predicted positives that are truly positive. Values closer to 1 means high precision and shows that there is a small number of false positives.
   Precision = True Positives
   True Positives + False Positives
   Recall is calculated as a proportion of actual positives that have been classified correctly. Values closer to 1 means high recall and shows that there is a small number of false negatives.
   Recall = True Positives
   True Positives + False Negatives
   Accuracy measures proportion of number of correct predictions to total number of samples. It helps to detect over-fitting problem (models that overfit have usually an accuracy of 1).
   Accuracy = Correct Predictions
   Total Predictions
   F1 Score combines precision and recall metrics by calculating their harmonic mean.
   $F1=2 * Precision * Recall$
   Precision + Recall
2. Log-Loss, Log-Loss Reduction
   Logarithmic loss quantifies the accuracy of a classifier by penalizing incorrect classifications. This value shows uncertainty of prediction using probability estimates for each class in the dataset. Log-loss increases as the predicted

probability diverges from the actual label. Maximizing the accuracy of the classifier causes minimizing this function.

Logarithmic loss reduction (also called reduction in information gain - RIG) gives a measure of how much improves on a model that gives random prediction.Value closer to 1 means a better model.

3. Confusion Matrix, Micro-averages, Macro-averages

   Confusion matrix contains precision and recall for each class in multi-class classification problem.

   A macro-average computes the metric independently for each class and then take the average (treats all classes equally).

   A micro-average aggregates the contributions of all classes to compute the average metric.

   Micro- and macro-averages may be applied for every metric.

   In a multi-class classification problem, micro-average is preferred because there might be class imbalance (significant difference between number of class examples).

9. Advantages and Disadvantages

9.1 Advantages

Advantages for weather forecasting in agriculture:

For example, weather forecasting enables you to properly plan your farm operations, such as planting, irrigation, fertilizer application, pruning/weeding, harvesting or livestock mating, since farming and agriculture as a whole chiefly depend on seasons and weather.

9.2 Disadvantages

Model Limitations: Forecasting models can only make predictions based on existing data and are limited by the quality and quantity of that data. Limited Time Frame: Forecasts are usually only accurate for a short time frame, making it difficult to plan ahead.

10. Conclusion

In summary, weather forecasts are increasingly accurate and useful, and their benefits extend widely across the economy.

11. Future Scope

In addition to predictions of atmospheric phenomena themselves, weather forecasting includes predictions of changes on the Earth's surface climate. These changes are caused by atmospheric conditions like snow and ice cover, storm tides, and floods.

12. Appendix

12.1 Source Code

```
from flask import Flask, render_template, request, url_for
import os
from flask import flash,redirect
from werkzeug.utils import secure_filename
import os
import shutil
from PIL import Image
from tensorflow import keras
```

```
from keras.layers import Dense
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    print(filename)
    file.save(os.path.join(app.config['UPLOAD_FOLDER'], filename))
    path = 'static/{}'.format(filename)
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    result = predict_model(img)
    return render_template('res.html', image_url=url_for('static',
filename=filename),result = result)

if __name__ == '__main__':
    app.config['UPLOAD_FOLDER'] = 'static'
    app.run(debug=True)
```

12.2 GitHub & Project Demo Link

https://github.com/smartinternz02/SI-GuidedProject-609761-1700581963