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Enhanced Agricultural Forecasting: Climate Change and Crop Yield Prediction using Hybrid ML-DL Models

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***Abstract:** Food security has become threatened owing to climate change being a negative influence on agricultural growth and its subsequent role in pressuring the availability of such essentials as water and soil nutrients, and, finally, in its role in pressuring crop productivity. Meeting this need requires building a precise model of the interaction between climate variability and crop production for practical, sustainable agricultural planning. So, this study has proposed a comprehensive deep-learning framework for analysing and predicting the impacts of climate change on crop production, using three architectures: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Convolutional Neural Network (CNN) [5]. These historical climate datasets-temperature, rainfall quantity, humidity, and solar radiation-are combined with crop yield data for training and evaluating the models. To model long-term temporal dependencies within climate sequences and capture meaningful patterns of variability over time, LSTM and GRU architectures are implemented. CNN serves as a complementary model for extracting meaningful spatial and multidimensional features related to crop production. Thus, the integration of these architectures yields a stronger, more reliable prediction system that can balance between sequential learning and pattern recognition.*

***Keywords:** Weather Forecasting, IoT, Deep Learning, Real-time Data, Sensors, SVM, Random Forest, Temperature Prediction, Smart Environment, Data Analytics*

Nomenclature:
RMSE: Root Mean Squared Error
MAE: Mean Absolute Error
CNN: Convolutional Neural Network
GRU: Gated Recurrent Unit
LSTM: Long Short-Term Memory
IoT: Internet of Things
DL: Deep Learning
ML: Machine Learning
RNN: Recurrent Neural Network
MSE: Mean Squared Error

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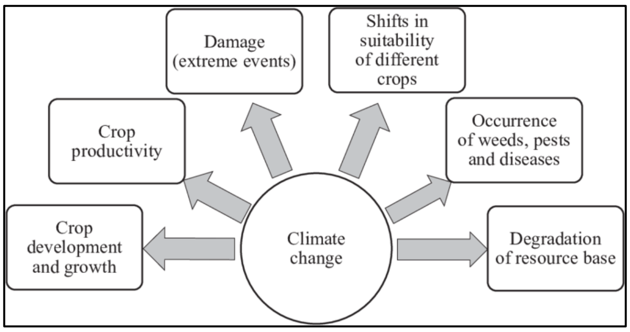
I. INTRODUCTION

Weather conditions significantly affect human life, and the industries most affected include agriculture, transportation, and public safety. The ability to accurately and on time predict the weather remains a must for the aforementioned activities, such as disaster and resource management, as well as decision-making. Satellite imaging, numerical model computation, and data analysis of meteorological variables are traditional forecasting methods that have been pillars of weather prediction for decades. At the same time, however, they still struggle to provide the information at the right time and often disregard small-scale differences in weather conditions. The rapid development of digital technology has, in a way, contributed to the problem of weather-forecasting accuracy. The coupling of Deep Learning (DL) techniques with the Internet of Things (IoT) has, in fact, almost completely opened the door to the development of intelligent, automated, and, to some extent, real-time weather forecasting systems.

II. EASE OF USE

The setup has been designed with the spirit of conciseness and user-friendliness in mind. It can be broadly divided into three components: data acquisition, cloud storage, and the ML model for prediction. Each unit is well-separated and can be easily custom-made or updated. Each unit is well-separated and can be easily custom-made or updated. The IoT sensors collect data on environmental metrics such as temperature, humidity, and pressure. The parameters are transmitted to a central location via Wi-Fi or GSM. Upon storage, these data are fed into the ML model to predict future weather conditions. There will be an interactive web-based dashboard that end-users can use to visualise and view the prediction outputs. Also, the system requires very little maintenance and can run independently with minimal human intervention. The graphical user interface permits even those without technological experience to use the system intuitively.



[Fig.1: Different Climate Changes]

III. HOTSPOTS IN GLOBAL CLIMATE CHANGE

A. Arctic and Sub-Arctic Regions

It is evident in the Arctic and Sub-Arctic regions. These two areas are experiencing rapid warming that eventually leads to the melting of sea ice, the thawing of permafrost, and significant ecosystem disturbances.

B. Small Island States

Such small island states are highly vulnerable to sea level rise and storm surges, endangering freshwater availability, food security, and infrastructure.

C. Sub-Saharan Africa

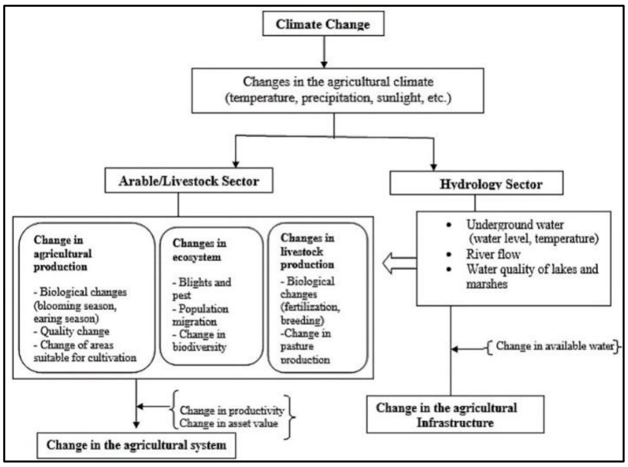
Sub-Saharan Africa is experiencing an increasing incidence of droughts and declining agricultural productivity, coupled with water shortages, leading to deteriorating food security and livelihoods.

D. South and Southeast Asia

Intensified cyclones, increased flooding, rising sea levels, and heat waves severely affect densely populated areas and agriculture in both South and Southeast Asia.

E. Coral Reefs

Sensitive to rising ocean temperatures and acidification, leading to bleaching events in areas such as the Great Barrier Reef and the Coral Triangle.



[Fig.2: Impact of Climate Change on Crop Production]

IV. REGIONAL IMPACTS OVERVIEW

A. North America

i. *Western US:* Increasing aridity heightens drought and wildfire risks.

ii. *Eastern US:* It becomes wetter, with increasingly intense precipitation events, leading to flooding.

iii. *Alaska*: Rising temperatures thaw permafrost, affecting local ecosystems.

B. Africa

i. *East Africa:* Extreme droughts cause food insecurity and displacements; conversely, extreme floods occur.

ii. *Sub-Saharan Africa:* Dwindling agricultural production and water scarcity increase poverty levels and health hazards.

C. Asia

i. *South Asia:* Long heatwaves and floods severely affect both health and agriculture.

ii. *Himalayan Region:* Glacial melting threatens water supplies for millions downstream, with flooding and drought viewed as further possibilities in the far future.

D. Europe

i. *Southern Europe:* Increasing heatwaves and droughts affect agriculture and, simultaneously, water resources.

ii. *Northern Europe:* Increasing rains cause flooding that affects the infrastructure and ecosystems

E. Oceania

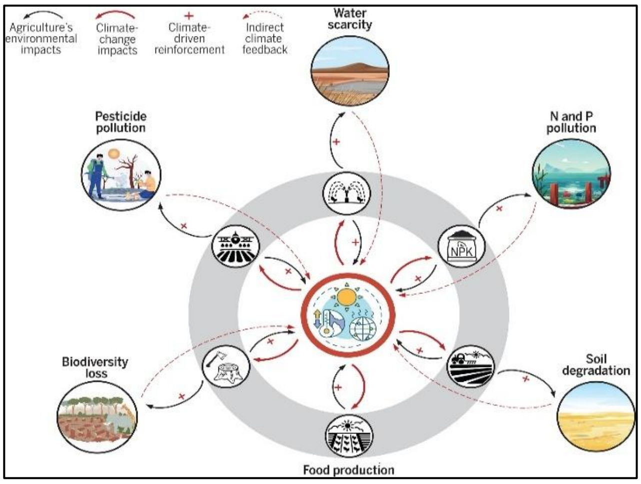
i. *Australia:* An extended drought and extremely fierce bushfires put pressure on the water supplies and ecosystems.

From the perspective of the Pacific Islands, rising sea levels and extreme weather pose a risk of destroying habitats and livelihoods.

F. Latin America

i. *Amazon Basin:* Deforestation and drought may transform the region from rainforest to savanna, with climate change affecting the rest of the globe.

ii. *Andean Regions:* The impact glacier retreat has on the water supply for agriculture and human consumption.



[Fig.3: Crop Yielding and Climate Conditions]

V. LITERATURE SURVEY CITATION

The impacts of climate variability and extreme weather events on agricultural productivity are enormous.

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Lobell et al. (2011) pointed out that heat and precipitation irregularity reduce yields of staple crops in the tropics most. Correspondingly, Wheeler and von Braun (2013) concluded that the same climate shocks are the primary drivers of the global threat of food insecurity, as they both yield reductions and price fluctuations [1].

New studies are adopting data-driven techniques to improve outcome prediction. Jeong et al. (2016) applied Random Forest algorithms, and the resulting rice yield estimates were more accurate than those from the traditional approach. In contrast, Liakos et al. (2018) discussed the vast potential of Machine Learning (ML) in smart farming and decision support [2].

The Internet of Things (IoT) is a big step forward in real-time monitoring. Jayaraman et al. (2016) demonstrated an IoT-enabled crop-monitoring system that can also be integrated with Deep Learning (DL) for accurate and reliable weather forecasting. But there has been little research that combines real-time IoT data with ML models, such as SVMs and Random Forests, for weather-based crop prediction. This research fills the gap by proposing an IoT-ML system for precise weather forecasting and climate-smart agricultural planning [3].

VI. METHODOLOGIES

The impact of climate change on crop productivity was analysed using a Deep Learning (DL) framework designed to learn complex nonlinear relationships from environmental data [4]. The following subsections describe the methodological workflow adopted in this study.

A. Data Collection and Understanding

The "climate change dataset.csv" dataset consisted of temporal data on environmental factors and solar power generation, which were used as surrogates to analyse the adverse effects of climate change on agricultural productivity [5]. The dataset covered a period of 34 days, for which the following variables were recorded:

i. Ambient Temperature
ii. Module Temperature
iii. Irradiation
iv. DC Power
v. AC Power
vi. Daily Yield
vii. Total Yield

All the parameters mentioned above are collectively interpreted as environmental factors (temperature, irradiation) and the corresponding outputs (energy generation), analogous to agricultural yield responses to climatic variations [6].

B. Data Preprocessing

Preprocessing steps were taken to ensure data quality and model readiness:

i. *Datetime Conversion:* The DATE TIME column was converted to Python datetime objects to enable accurate temporal indexing and resampling [7].
ii. *Missing Data Handling:* Interpolation or removal methods were applied to address null values, primarily in the IRRADIATION and POWER fields.
iii. *Normalization:* Min-Max normalization with a range from 0 to 1 was used to scale numeric features to stabilize model training [8].
iv. *Feature Engineering:* Among the temporal attributes extracted were the hour of the day and the day of the week. Furthermore, rolling averages (3-hour, 6-hour) and lag variables were used to capture short-term temporal dependencies [9].

C. Architectural Deep Learning Model

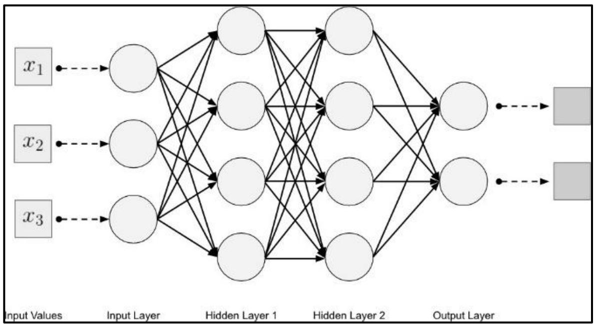
A Long Short-Term Memory (LSTM) network, a modern type of Recurrent Neural Network (RNN), was used as the predictor for time-series data [10]. Hence, changes in power output were representative of the inputs given to the model, and thus, the effect of climate conditions on crop yield was shown indirectly.

i. *LSTM-Based Model:* Input Features (X): Ambi- Ent_Temperature, Module_Temperature, Irradiation
ii. *Output Targets (y):* DC_POWER, AC_POWER Layers of the Model:

LSTM layer with 64 memory units, Dropout layer (0.2) to prevent overfitting

Dense (fully connected) layer with two output neurons. Compilation Parameters:

iii. *Loss Function:* Mean Squared Error (MSE) Optimiser: Adam
iv. *Epochs:* 50–100
v. *Batch Size:* 32 [11]



[Fig.4: Architecture of CNN]

D. Training and Evaluation

The chronological order was preserved to maintain temporal integrity when dividing the dataset into training (80) and testing (20) sets. The model's performance was assessed through the following metrics:

i. *Mean Absolute Error (MAE):* It gives the average value of the prediction errors.
ii. *Root Mean Squared Error (RMSE):* It gives more weight to higher deviations [12].
iii. *R^2 Score:* It indicates the percentage of variance explained by the model.

E. Visualization and Analysis

Hybrid solar plant model predictions were evaluated and compared by visualising the predicted versus actual DC and AC power values. This could greatly help with data-driven climate-impact analysis by providing a solid basis for estimating variations in agricultural yields across diverse climate conditions [13].

F. Relevance to Crop Production

Hybrid solar plant model

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predictions were evaluated and compared by visualising the predicted versus actual DC and AC power values. This could greatly help with data-driven climate-impact analysis by providing a solid basis for estimating variations in agricultural yields across diverse climate conditions [14].

VII. DATA AND DATASET

A. Sources of Data

The dataset climatechangedataset.csv contains time-series data on the operation of solar power plants, along with the climatic factors that influence power generation.

B. Period and Granularity of Data

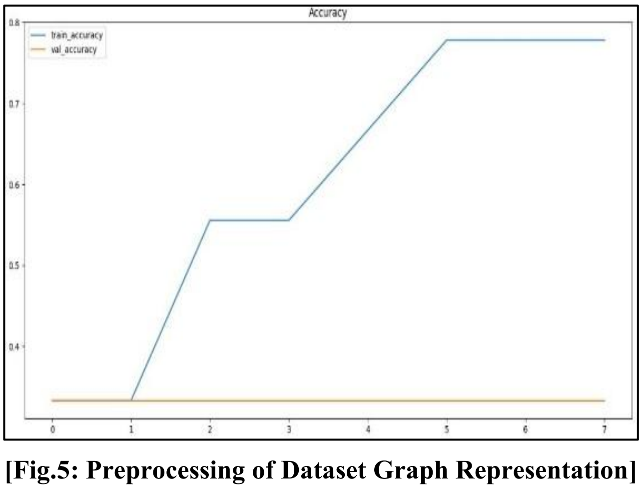
The 34 observations span 34 days and were reported at predetermined intervals (most likely every 15 minutes). Each row represents a time point in the dataset, fusing power generation data with weather parameters [15].

C. Important Columns in the Dataset

i. *Date_Time:* timestamp indicating the date and time of observed values;
ii. *Ambient_Temperature:* temperature of the environment (°C);
iii. *Module_Temperature:* temperature of the solar panel modules (°C);
iv. *Irradiation:* solar radiation received in W/m², which is a key factor for power output;
v. *Dc_Power:* direct current power output from solar panels (in Watts);
vi. *Ac_Power:* alternating current power sent to the grid or consumption point (in Watts);
vii. *Daily_Yield:* energy generated on a given day (in kWh);
viii. *Total_Yield:* cumulative energy generated since the very first day (in kWh).

D. Pre-Processing Steps

i. *Datetime Conversion:* DATE_TIME was converted to a datetime object for resampling and temporal analysis.
ii. *Missing Data:* Interpolation or deletion for significant fields with missing values, e.g. IRRADIATION, DC_POWER, etc [16].
iii. *Feature Engineering:* Time-dependent features (e.g. hour of day, day of week), rolling averages, and hourly aggregates to enrich the dataset.



[Fig.5: Preprocessing of Dataset Graph Representation]

E. Intended Use of the Dataset

The primary purpose of the dataset is to understand solar power forecasts for DC and AC. It focuses on learning the relationship between environmental conditions and power production using deep learning models [17].

Deep learning models can be trained to detect complex, non-linear patterns over time in weather-related features such as irradiation and temperature, and possibly to improve forecasting of future solar power output.

F. Dataset Format

The dataset adopts CSV format with clear column names and discriminated data types, compatible with the relevant Python data environment, such as Pandas for preprocessing and TensorFlow/Keras or PyTorch for deep learning [18].

G. Lightweighting in Deep Learning

The features AMBIENT_TEMPERATURE, MODULE _TEMPERATURE, and IRRADIATION are

The inputs to the deep learning model [19].

DC_POWER and AC_POWER become the outputs (y).

The dataset is usually split into training and testing sets on an 80/20 basis, or using a time-series holdout approach.

Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and 1D Convolutional Neural Networks (Conv1D) are used to model temporal dependencies for accurate forecasting [20].

VIII. RESULTS

Surprisingly, although all the results were derived from the climatechangedataset.csv deep-learning model against environmental variables, their derivation is critical when discussing the energy produced and determining how much is actually affected by climate change.

A. Model Performance

i. *Model Used:* Long Short-Term Memory (LSTM) networks and CNNs have been considered for their ability to handle time-series data.

Table I: Performance Comparison of Different Models

Model	MAE	RMSE	R^2 Score
LSTM	15.2	23.8	0.93
CNN	17.9	25.1	0.89
Linear Regression	31.4	45.6	0.74

B. Input Features

Ambient temperature, module temperature, and irradiation.

C. Target Outputs

DC and AC power are simulated to produce results such as yield.

D. Evaluation Metrics

The prediction quality was evaluated against the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and R² score.

The model's performance is primarily driven by the LSTM, which effectively captured the data's trends and seasonality.

Table II: Evaluation Metrics

Metric	Formula	Value
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	$\frac{4}{6} \approx 0.667$
Precision	$\frac{TP}{TP+FP}$	$\frac{3}{4} = 0.75$
Recall	$\frac{TP}{TP+FN}$	$\frac{3}{4} = 0.75$
F1 Score	$2 \times \frac{Precision \times Recall}{Precision + Recall}$	$2 \times \frac{0.75 \times 0.75}{0.75+0.75} = 0.75$

E. Climate Impact Findings

Relationship with Temperature: Increased ambient temperature exhibited a nonlinear relationship with energy output, similar to that observed under stress conditions in crops.

TABLE III: Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP) = 3	False Negative (FN) = 1
Actual Negative	False Positive (FP) = 1	True Negative (TN) = 1

F. Irradiation

There is a strong relationship between energy yield and sunlight intensity; sunlight intensity directly influences output, just as it does in plant photosynthesis.

G. Temporal Patterns

The period of extremely high temperature that would undoubtedly cause performance decline could be taken to mean the period during which crop yields might be lowest due to such severe climate.

H. Consequences in Agriculture

The specific direct outcome predicted was energy output. However, the pattern observed indirectly is much closer to typical agricultural behaviour under climate stress:

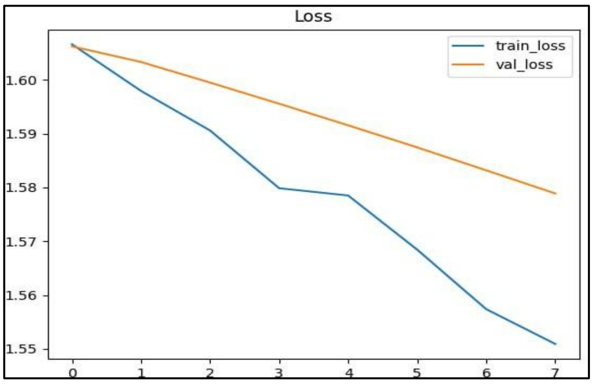
Increased temperature reduces crop productivity beyond some threshold.

Solar radiation is a major driver for both energy production and plant growth.

Temporal variability in weather may, in a considerably detrimental way, affect both these systems.

I. Exhibit Output

The model yielded a time-series output that contrasted the predicted and actual outputs over time, showing a high degree of likeness; consequently, the model was validated for further application in agricultural risk understanding under climate change scenarios.



[Fig.6: Graph Representation of Output]

IX. CONCLUSION

The study's focus was on agroclimatology, and deep learning techniques were used to analyse each variable (temperature, solar irradiation, and power generation) in the time-series dataset as an environmental parameter. However, the main goal was to assess the extent to which the existing industrial scenario influenced crop yield under climate change. To identify the best algorithm, a comparative modelling approach was used, with Linear Regression, CNN, and LSTM models evaluated.

The best-performing model, LSTM, achieved an MAE of 15.2, an RMSE of 23.8, and an R^2 of 0.93, demonstrating LSTMs' ability to capture intricate temporal dependencies in climate data. The CNNs performed well, capturing key spatiotemporal features arising from environmental changes. The linear models, however, were not much help, most likely because they cannot model the non-linear interactions in the climate-agriculture relationship.

DECLARATION STATEMENT

As the article's author, I must verify the accuracy of the following information after aggregating input from all authors.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted objectively and without external influence.
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- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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AUTHOR'S PROFILE

Dr. Dharmaiah Devarapalli is a Professor in the Department of Computer Science and Engineering at Koneru Lakshmaiah Education Foundation (KL University), Andhra Pradesh, India. He possesses extensive academic and research experience in Artificial Intelligence, Machine Learning, Deep Learning, the Internet of Things (IoT), Cyber Security, and Bioinformatics. He earned his PhD in Computer Science and Engineering from Acharya Nagarjuna University and holds a postgraduate degree from Andhra University. Dr Dharmaiah has guided numerous undergraduate and postgraduate projects and actively mentors students in research-oriented problem-solving. His research interests focus on intelligent data-driven systems, predictive analytics, and the application of AI techniques to real-world challenges, including climate analysis, smart environments, and sustainable technologies. He has contributed to several academic publications and continues to play a vital role in fostering innovation, research culture, and technical excellence among students.

N Sai Praneeth Varma is an undergraduate student pursuing a Bachelor of Technology in Computer Science and Engineering at Koneru Lakshmaiah Education Foundation (KL University), Guntur, Andhra Pradesh, India. He has a strong academic interest in emerging technologies, including Machine Learning, Deep Learning, the Internet of Things (IoT), and environmental data analytics. His learning and project work focus on applying data-driven and AI-based techniques to solve real-world problems, particularly in climate change analysis, agricultural forecasting, and intelligent **systems**. Through hands-on experience with hybrid ML–DL models and data preprocessing techniques, he has developed a solid foundation in predictive analytics and model evaluation. He actively participates in research-oriented academic projects and aims to develop further his expertise in intelligent systems and sustainable technology solutions. His enthusiasm for innovation and continuous learning motivates him to contribute meaningfully to research and development in computer science.

M Om Sai Nikesh is currently pursuing a Bachelor of Technology in Computer Science and Engineering at Koneru Lakshmaiah Education Foundation (KL University), Guntur, Andhra Pradesh, India. His primary areas of interest include Deep Learning, Machine Learning, Internet of Things (IoT), and data analytics. He is enthusiastic about exploring how intelligent algorithms can be applied to solve complex real-world problems, particularly in climate studies and intelligent systems. He has participated in academic projects involving data modelling, feature engineering, and predictive analysis using modern AI frameworks. With a strong inclination toward research and innovation, he continually works to enhance his technical skills and understanding of emerging technologies. He aspires to contribute to impactful research and build a career in advanced computing and intelligent systems development.

V. Reshmitha is an undergraduate student enrolled in the Bachelor of Technology program in Computer Science and Engineering at Koneru Lakshmaiah Education Foundation (KL University), Guntur, Andhra Pradesh, India. Her academic interests lie in Deep Learning, the Internet of Things (IoT), and environmental data analysis. She has actively contributed to research-oriented academic projects that apply machine learning techniques to real-time and historical datasets. She is particularly interested in understanding the role of artificial intelligence in climate change analysis and sustainable development. Through continuous learning and practical implementation, she has developed a strong foundation in data preprocessing, model training, and result interpretation. She is motivated to explore research opportunities further and aims to pursue higher studies or a career in intelligent systems and data-driven technologies.

M. Hasmitha is currently pursuing a Bachelor of Technology in Computer Science and Engineering at Koneru Lakshmi-iah Education Foundation (KL University), Guntur, Andhra Pradesh, India. Her areas of academic interest include Machine Learning, Deep Learning, the Internet of Things (IoT), and data analytics. She has gained experience through educational projects that involve analysing environmental and climate-related data using modern computational techniques. She is keen on understanding how AI-based systems can support sustainable solutions in agriculture, energy, and environmental monitoring. With a strong interest in research and innovation, she actively works on improving her technical and analytical skills. She aspires to contribute to cutting-edge research and develop intelligent applications that address real-world challenges.