ABSTRACT

Agricultural workers are one of the highest risk groups identified for extreme heat exposure, which can have negative health, safety and productivity impacts. This research study focuses on developing an intelligent forecasting system dubbed "Heat Stress Category Forecast for Farm Labour" which aims to classify and predict the level of heat stress for farm labourers in various climate conditions. This research examines meteorological and environmental variables such as temperature, humidity and rainfall in order to generate various useful thermal comfort indices including Mean Temperature, Dew Point, Wet-Bulb Temperature, Heat Index, and WBGT (Wet Bulb Globe Temperature) Proxy. A robust data preprocessing pipeline was implemented to improve data quality via methods such as missing values, outlier corrections (by IQR), removing duplicates, unit checks, and temporal validation using time based train-test splits.

Predictive performance improved in later feature engineering when lag features, time-related patterns, rolling averages, and interaction terms were added.. Once data were labelled into categories of heat stress affected and not affected, multiple machine learning and deep learning models were applied. These models ANN, RNN, LSTM, Bi-LSTM. The models were assessed in order to identify the most robust framework that could accurately forecast heat stress categories. In addition, this project expands to temporal trend analysis to observe heat stress differences across seasons, and spatial extraction, in order to visualize the area affected at different locations. The proposed system will provide useful information for early warning, risk assessments, and heat stress management, and thus farm labour welfare, with sustainable agricultural practice under continuously changing climate conditions.

Keywords

Heat Stress Forecasting, Farm Labour, WBGT, Heat Index, Deep Learning, Temporal Analysis, Spatial Extraction, Data Preprocessing, Feature Engineering.

CHAPTER 1

INTRODUCTION

Agriculture is critical for rural livelihoods and consists of millions of farm labourers working daily in difficult environmental settings. While there are many occupational hazards associated with this work, the hazard of heat stress in a changing climate and states of extreme heat or heat waves are becoming more prominent in some areas. Extended time spent in high temperatures has the capacity to contribute to fatigue, dehydration, and serious heat-related illness that threaten farm workers' occupational safety and health as well as agricultural productivity. Thus, there is priority to monitor, classify, and characterize heat stress to protect the health of farm workers and sufficiently promote sustainable farming practices.

Forecasting Heat Stress Category for Farm Labour is a project focused on constructing an intelligent model to classify and predict the heat stress category using weather and environmental conditions. The dataset utilized to create these indices are derived from NASA POWER (2010-2025) and includes climate attributes essential to technical performance such as temperature, humidity, precipitation, pressure, and wind speed. The data was cleaned and processed with extensive practices including dealing with missing values, correcting for outliers, checking unit consistency, and maintaining temporal accuracy through time series based data splits. Other heat indices that represent some of the physiological impacts of heat stress exposure of farm workers such as Mean Temperature, Dew Point, Wet-Bulb Temperature, Heat Index, and WBGT Proxy, were computed and incorporated into the study.

In order to enhance the prediction capabilities, some sophisticated feature engineering methods were used, including lag variables, rolling mean, and temporal interaction. A range of machine learning and deep learning algorithms like Auto ARIMA, SVM, Bi-LSTM, GRU, ANN, CNN, Random Forest, and so forth were implemented and assessed for classification performance. Among them, the Support Vector Machine (SVM) model performed the highest and was also applied for temporal trend analysis and spatial extraction. The results indicated distinct season and regional differences in heat stress, with monsoon and summer seasons having the highest risk levels and areas such as Thoothukudi and Ramanathapuram being among the most affected regions. In sum, this research provides a data-driven framework for the prediction of heat stress in order to contribute to early warnings, evidence-based policy intervention, and improved occupational safety among agricultural laborers.

1.1 BACKGROUND KNOWLEDGE

Climate change is resulting in temperature extremes that are creating more frequent and intense heatwaves in many areas of the world. This change represents a serious risk for outdoor workers, especially for outdoor workers in agriculture who are particularly vulnerable to the varying weather conditions of climate change. Heat stress occurs when the body is unable to keep a regulated core body temperature for a prolonged period of time due to high temperatures or prolonged exposure to high humidity, which can result in a decrease in physical performance and serious health complications. It is crucial to understand and assess heat stress in order to protect the health, safety, and productivity of farm workers that underpin many agricultural economies.

Due to the complex nature of heat stress, measuring it accurately requires assessing multiple metrological variables including air temperature, relative humidity, wind speed, precipitation, and surface pressure. Over the decades many thermal comfort indices have been created including the Heat Index, Wet-bulb Globe Temperature (WBGT), and Dew Point Temperature that do a good job of measuring the thermal response of the human body to the physical environment. By combining these thermal comfort indices with historical climate data it is possible to estimate and forecast temperatures which may be heat stressed temporally and spatially. Data from reputable datasets such NASA POWER provides researchers with access to high-valued, historical meteorological variables necessary for creating robust predictive models.

Environmental data becomes available and computational techniques improve, machine learning and deep learning algorithms have become strong contenders for analyzing intricate climate-health dynamics. Algorithms such as Support Vector Machine, Recurrent Neural Networks, Long Short-Term Memory, and Convolutional Neural Networks can learn temporal patterns and nonlinear associations between climatic factors and the endpoints of heat stress. These models not only allow for efficient classification of non-affected and affected persons but also enable temporal prediction and spatial mapping of heat stress exposure. Therefore, the convergence of environmental science with artificial intelligence enables a solid framework for predicting heat stress risks as well as encouraging adaptive measures for agricultural resilience and worker well-being.

1.2 PROBLEM STATEMENT

The increasing frequency of extreme heat events under a changing climate endangers the health, productivity, and safety of farm workers who are in direct exposure to extreme weather conditions. Prolonged exposure to heat may result in heat-related illnesses, dehydration, and further serious consequences. Current heat stress monitoring systems do not identify and categorize heat stress levels based on fluid conditions. Thus, this project will develop an intelligent "Heat Stress Content Forecasting System for Farm Labour" that uses meteorological variables including temperature, humidity, wind speed, rainfall, and pressure along with advanced machine and deep learning models to classify workers as experiencing heat stress or not and identify both temporal and spatial patterns to warn of heat stress and take preventative measures.

Addressing these challenges requires:

1. Integration of climatic and environmental data that include all the meteorological variables in one platform, including temperature, humidity, wind velocity, and rainfall, to correctly portray the environmental conditions which cause heat stress.
2. Implementation of advanced predictive models that utilize robust machine learning and deep learning methods to classify and predict heat stress categories with high accuracy to provide timely and trustworthy predictions to act preventively.
3. Spatial-Temporal analysis for decision support that combines both temporal trends and spatial distribution analysis in order to identify regions and time periods that are at high-risk, which informs targeted policy interventions and improved safety management for farm labourers.

1.3 OBJECTIVES

In order to predict and examine heat stress classes of farm workers in Tamil Nadu, the following are the guiding objectives for framing a robust predictive and analytical framework:

The project initially seeks to determine the prevalence of heat stress on farm workers by evaluating main meteorological factors like temperature, humidity, wind speed, rainfall, and surface pressure from NASA POWER's 2010–2025 daily dataset. The occupational hazard of exposure to extreme heat is measured in the study by categorizing workers into "affected" and "not affected."

The study purpose is to analyze temporal patterns in heat stress and unveil seasonal and annual variability. For example, seasons such as summer and monsoon seasons ought to record increased heat stress rates, while winter shows comparatively lower effects. The temporal evaluation provides important insights into how climate change changes the safety and productivity of farm workers over time.

1. Moreover, the initiative emphasizes spatial extraction and hotspot analysis, assessing the spread of heat stress within districts in Tamil Nadu. Thoothukudi, Ramanathapuram, and Thiruvarur are identified as high-risk areas and Theni and Coimbatore experience much lower heat stress.
2. Lastly, the study aims to create a strong prediction support system to foreshadow future heat stress conditions by developing and comparing different machine learning and deep learning models-including SVM, Bi-LSTM, GRU, ANN, and others. This would allow for the development of early-warning systems, policy and preventive interventions, and techniques to protect farm laborers from the increasing risks of heat stress.

CHAPTER II

REVIEW OF LITERATURE

Chapman et al. (2023) established a deep learning framework for calculating the occurrences of heat stress in cattle using climatological and physiological data. The framework is applicable for prediction of heat stress and outperformed established regression models. Thermal sensation was defined using environmental conditions, behavior, and thermal conditions (environmental- temperature, humidity, etc.; animal - behavioral response). The authors' work exemplifies the potential for AI in precision livestock production through unique and timely identification of stress. It should be noted th their study took into account a more controlled farm setting, and so the generalizeability outside of that farm context is limited [1].

Sharma et al. (2024) conducted a comparative assessment of numerous machine learning techniques for crop yield prediction. In the research, the authors evaluated models including Random Forest (RF), Support Vector Machine (SVM), and XGBoost using agricultural field datasets from various climate settings. It was found that ensembles performed better than linear methods when predicting crop yield under climate variation. While the authors ended their report with an emphasis on data preprocessing and feature selection enhanced prediciton performance, it was noted this study was limited by the absence of real-time data for dynamic forecasting [2].

Wang et al. (2023) applied citizen science and machine learning in developing high-resolution mapping of urban heat exposure. The study combines satellite data, in situ sensors, and crowdsourced temperature data to capture microclimate variability. Machine learning algorithms identified hotspots of urban heat stress at higher spatial resolution. This provided a useful approach for climate monitoring driven by the community. However, temporal consistency and data reliability remained challenges for continuous mapping [3].

Ojha et al. (2024) propose a worker-centric method of analyzing heat strain using physiological sensors and ensemble learning. The proposed work will combine heart rate, skin temperature, and motion data to predict an individual's heat stress level. The model will also benefit from domain adaptation to generalize fully to different work environments. Such a framework enhances occupational safety monitoring in extreme temperatures. However, sensor calibration and individual variability remain some of the key concerns [4].

Delfani et al. (2024) this research integrated IoT, machine learning, and AI tools to predict agricultural diseases due to climate change. Delfani et al. highlighted the potential benefits of real-time environmental sensing and predictive modeling for proactive disease management. The framework has supported adaptive decision-making in precision agriculture. Strong model performance in the detection of early disease onset was realized. However, the authors have indicated a need for scalable data infrastructure across diverse agro-climatic regions [5].

Ali et al. (2024) applied machine and deep learning techniques to identify crop drought stress from remote sensing and meteorological data. Models such as CNNs and Random Forests achieved excellent accuracy in identifying stressed vegetation. The study demonstrated how AI-driven analysis can support smart agriculture and resource optimization. Their results showed promising applications for early drought warnings. A limitation noted was model dependence on high-quality, labeled datasets [6].

Sulzer and Christen (2024) conducted an assessment of climate projections to evaluate human thermal comfort in a variety of indoor workspaces. The research involved using climate models and comfort indices, specifically, PMV and PPD indices to model projections of future heat stress scenarios. The authors found their results indicated an increase in discomfort and productivity loss when confronted with increasing temperature exposure. Their paper discussed the implications of these findings for future building design and ventilation systems, and emphasized how building design needs to adapt to temperature extremes. However, the results of these studies did not consider the effects of individual physiological responses of the human body to heat exposure [7].

Pal and Patel (2025) investigated physiological responses to heat stress in rice transplanting workers in Northeast India. They measured core temperature, heart rate, and work-rest schedules under maximum heat exposure. Authors reported strong evidence of thermal strain to heat exposure in participants, and provided alternative work-rest schedules to provide greater safety for workers in job activity. Their research also provides insights and practical strategies for managing occupational heat exposure in agricultural work, however, the scope of their findings were limited to the region and type of workers [8].

Choi et al. (2024) produced a machine learning model to estimate heat exposure time based on extreme heat events. The model used both environmental and physiological variables in its calculations of work time under heat stress. The use of deep learning and ensemble methods showed robust predictive accuracy for forecasting. They underscore the implications for a framework with providing practical strategies for defining adaptive standards for heat exposure in workers. The study findings, however, were all from controlled experiments where variability in both subject and environment are absent [9].

Kato et al. (2025) measured occupational heat stress in environments without set safety standards based on data from wearable biosensors. In this work, collective physiological signals were used to assess real-time thermal strain among workers. Indeed, these results indicated the possibility of using biosensor-based monitoring for occupational health. In this respect, the authors used both statistical methods and machine learning techniques to effectively classify stress levels. However, they identified serious challenges, including data privacy and sensor reliability [10].

Rebez et al. (2024) reviewed applications of artificial intelligence for heat stress management in ruminant livestock. This paper presented the use of AI and IoT systems in monitoring animal welfare through temperature, respiration, and behavioral parameters. It compared various predictive models involved in livestock management. The study highlighted the capabilities of AI in mitigating productivity loss resulting from thermal stress. However, scaling up to real-time implementation in large herds remains an open challenge [11].

Xu et al. (2024) applied machine learning to analyze the meteorological factors affecting the occurrences of urban heatstroke. This study integrated data on temperature, humidity, wind speed, and air pollution to predict disease incidence. Gradient boosting and neural networks showed high predictive accuracy regarding the risk of heat-related illnesses. The model serves as a public health decision-support tool, but it may perform differently under different conditions with spatial and temporal limitation of data [12].

Zhang and colleagues (2024) investigated the association between discomfort temperature and productivity loss for petroleum and chemical workers. They tested machine learning and deep learning models to measure the reduction in efficiency from increased temperatures in the workplace. Zhang and collaborators found a strong relationship between discomfort temperatures and multiple performance measures. In the study, AI proved to be effective for application in industrial ergonomics and occupational safety. The study limitations included industry-specific data and short durations of measurement [13].

CHAPTER 111

RESEARCH METHODOLOGY

3.1 Data Collection

The data utilized for this project was sourced from the NASA POWER (Prediction of Worldwide Energy Resources) database, which offers high-resolution, satellite-based meteorological data ideal for climate and environmental research. The dataset extends from 2010 to 2025 and contains daily data of crucial atmospheric variables, which include minimum and maximum temperature, relative humidity, precipitation, wind speed, and surface pressure from several districts in Tamil Nadu. A robust, comprehensive dataset was selected for its dependability to provide global coverage and time consistency for longitudinal assessments of climate trends. These climate variables are the key inputs into models and forecasts for heat stress levels faced by farm labourers, given their direct influence on thermal comfort and environmental heat exposure in agricultural systems.

1. SOURCE OF THE DATA

The data is presented in a study that uses the NASA POWER (Prediction Of Worldwide Energy Resource) platform, which is a trusted global source for high-resolution meteorological environmental data. The data are daily climate data from 2010 to 2025 for several districts in Tamil Nadu, India. The sought parameters include air temperature (maximum and minimum), relative humidity, wind speed, surface pressure, and precepitation that are important to analyzing heat stress conditions. The data were obtained from the NASA POWER Data Access Viewer (DAV), which combines satellite based observtions and model-derived outputs from the Modern-Era Retrospective Analysis for Research and Applications (MERRA-2). This dataset was reliable and considered to be scientifically validated and forms the basis for the heat stress forecasting and classification models in this study.

2. DATASET COMPOSITION

The monitoring locations for this project in Tamil Nadu are compiling daily weather readings from 2010 to 2025 from the NASA POWER (Prediction of Worldwide Energy Resource) database. Each district produced records for thousands of days and its climatic records capture relevant climate variables that affect heat stress conditions.

- Each recorded day is an observation, detailing key climate variables that impact heat stress conditions. The dataset mainly captures columns such as the Date, the District/Location of the attribute, the Minimum Temperature (t2m_min), Maximum

Temperature (t2m_max), Relative Humidity (rh2m), Wind Speed (ws2m), Precipitation (prectotcorr), and Surface Pressure (PS). Furthermore, several calculated variables were added that represent Mean Temperature, Dew Point, Wet-Bulb Temperature, Heat Index, and WBGT Proxy through the new, computed variables.

- In aggregate, these daily observations form a large data set that permits both classification of farm laborers' heat stress status (affected or unaffected) as well as spatial-temporal analysis of heat stress dynamics in the state.

3. DATA ATTRIBUTES

The dataset employed in this analysis encompasses important meteorological and derived thermal comfort variables that are essential for understanding and predicting heat stress in farm workers. Key variables from the NASA POWER in the dataset are:

- **t2m_min (Minimum Temperature) -** Indicates the lowest air temperature at or near the surface (°C).
- **t2m_max (Maximum Temperature)** – indicates the maximum daily air temperature (°C).
- **rh2m (Relative Humidity)** – Is the percentage of moisture in the air (%).
- **ws2m (Wind Speed)** - indicates the average wind speed at a height of 2 m above ground level (m/s), which impacts heat loss (or gain).
- **prectotcorr (Precipitation)** – Refers to the corrected total precipitation rate (mm/day), which influences cooling and humidity.
- **ps (Surface Pressure)** – Indicates the atmospheric pressure at the surface level (kPa or hPa), which relates to air density and temperature perception..

Included in this dataset are also several derived variables that were calculated in order to provide a better measure of physiological heat load on farm workers:

- **Mean Temperature -** Represents the average of the maximum and minimum temperature value to represent the total thermal load.
- **Dew Point Temperature** – is the temperature at which the air is saturated with water vapor, which is indicative of moisture and comfort level.
- **Wet-Bulb Temperature** – Is a commonly used measure that combines both temperature and humidity to describe heat measured by a human subject.

- **Heat Index** – It is an integrated heat measure that takes into account both temperature and humidity.
- **WBGT (Wet Bulb Globe Temperature) Proxy** – is a derived approximation of the WBGT index, which is a common heat stress index used to measure.

4. DATA FORMAT

The dataset used in the project is designed in the format of a tabular display with daily meteorological and environmental observations collected from NASA POWER for the time span 2010 to 2025. The dataset contains numerical and categorical information, along with some limited textual information describing spatial and temporal attributes. The data structure accommodates machine learning compatibility, temporal forecasting, and spatial analysis.

1. Numerical Data

The numerical parameters form the core of the dataset and are continuous meteorological and derived parameters that are used for heat stress prediction and classification. These include:

- **t2m_min** – Minimum temperature (°C)
- **t2m_max** – Maximum temperature (°C)
- **rh2m** – Relative humidity (%)
- **ws2m** – Wind speed (m/s)
- **prectotcorr** – Daily precipitation (mm/day)
- **ps** – Surface pressure (hPa)
- **Derived Indices** – Mean Temperature, Dew Point, Wet-Bulb Temperature, Heat Index, and WBGT Proxy

The above numerical parameters are scaled and normalized to improve the performance of machine learning algorithms such as SVM, LSTM, and Bi-LSTM.

2. Categorical Data

Categorical data reflects discrete classifications obtained from numerical variables and are important for supervised learning and labeling:

- **Heat_Stress_Label** – Classifies the heat stress levels into High, Moderate, and Low, based on indexes obtained.
- **Binary_Label** – Simplified indication means 1 = Affected and 0 = Not affected.

- **Season** – Indicates the climatic period (Summer, Monsoon, Post-Monsoon, Winter) used for analyzing patterns over time.

3. Textual Data

Textual attributes provide contextual and geographic information used to map spatially over time:

- **Date** – Observation date (YYYY-MM-DD) used for temporal analyses.
- **Place / District** – Specifies the monitoring area or district across Tamil Nadu. These textual fields are critical for linking climate variations with geographic areas and time, enabling spatial extraction and programmatic visualization of time-trend observations.

4. ADDITIONAL INSIGHTS

- The analysis showed clear seasonal and spatial variation in heat stress throughout Tamil Nadu. High rates of stress due to temperature and humidity appeared in the summer and monsoon seasons, while in winter there was temporary relief. A recent increase in the level of heat stress over the years depicts the consequence of climate change.
- Spatial analysis using the SVM model revealed that Thoothukudi, Ramanathapuram, and Thiruvarur are high-risk districts, while Theni and Coimbatore have low vulnerability. These findings highlight that there is a need for region-specific strategies in order to safeguard farm laborers.

Overall, this study shows how data-driven forecasting can be used in heat-related occupational risk management to support early warning systems and sustainable agricultural practice development.

3.2 DATA PREPROCESSING

Data preprocessing is essential for the accuracy and reliability of any predictive modeling process. It includes a large amount of preprocessing on the raw meteorological dataset downloaded from NASA POWER for the years 2010-2025 into a form that could suit analysis and model development.

1. STANDARDIZE / HANDLE COLUMN NAMES

- For example, all column names were made lowercase, any unnecessary spaces were eliminated, and any special characters were changed to underscores (e.g., “t2m max” became “t2m_max”). This allows consistency and improves readability while preprocessing and running models.
- A mapping of the original column names to the cleaned column names is maintained to ensure traceable and consistent workflow, avoiding errors in later stages of analysis.

2. DATATYPE CONVERSION

- DataType Conversion: This ensures that each dataset attribute is stored correctly in its proper format for proper analysis. In this project, date columns were converted to datetime format with standardized time zones so that date fields are consistent and uniformly dated. Numeric-like strings have been converted to either integers or floats. Invalid entries were coerced to NaN.
- Categorical variables such as locations and labels were defined as categorical types to improve computational efficiency. Validation using df.dtypes and df['date'].isna().sum() was performed, confirming proper conversion before analysis.

3. DATE/TIME INDEXING & FREQUENCY

- Time indexing: The date column was set to be the primary index and sorted in ascending order to maintain chronological order. In the case of datasets that support multiple districts, both place and date were used as a multi-index to support district-level temporal analysis.
- Frequency Standardization: Inferred the frequency of the data and then standardized it to a day using resampling to make the time intervals uniform. This aids in computing lag, rolling, and seasonal features accurately for time series forecasting.

4. INITIAL MISSING-VALUE ASSESSMENT

- Detection of missing values: We ran an initial assessment to detect missing values by calculating the total count and percentage of missing data for every column, to understand how much data was missing across all features.
- Visualizing missingness: Heatmaps or missing-value matrices were used to visually inspect patterns of missing data so that we could determine which columns required advanced imputation techniques, and which could be filled in simply or removed.

5. **OUTLIER DETECTION & CORRECTION**

- Identifying outliers: We examined outliers in numeric columns using the Interquartile Range (IQR) method, by flagging values beyond [Q1 - 1.5×IQR, Q3 + 1.5×IQR]. And visually inspecting the points in the time series helped us confirm whether those values were true variations or sensors recording erroneous values.
- Correcting outliers: The flagged outliers were corrected through, for example, interpolation, rolling median smoothing, or surrounding valid observations. If it was clear that some values represented sensor glitches, then the extreme values were replaced with NaN values and then actively coded in an imputation process to retain observation features, and avoid biasing model training and fitting.

6. **DUPLICATES & RECORD INTEGRITY**

- Duplicate Detection Exact duplicate records were detected by using df.duplicated().sum() to make sure data was unique. Potential duplicates, considering key attributes such as (date, place), were further checked for duplicate entries arising from multiple recordings or logging errors.
- Duplicate resolution: When duplicates were encountered, only the latest or average reading is retained, depending on data reliability. This step ensured that the record integrity was intact to avoid any biases or false weighting in model training and analysis.

7. **FEATURE ENGINEERING**

- Thermal Indices Computation: Physiologically relevant indices, namely Mean Temperature (Tmean), Dew Point (Td), Wet-Bulb Temperature (Tw), Heat Index, and WBGT Proxy, were calculated using the temperature, humidity, and pressure meteorological parameters for better representation of actual exposure to heat

- Purpose of Derived Features: These derived indices represent a more realistic measure of thermal discomfort and heat load on farm labourers, offering a stronger correlation with human heat stress compared to using raw temperature or humidity data in isolation.

8. **TIME-SERIES FEATURE ENGINEERING**

- Temporal Feature Construction: Features such as lag features (e.g., lag_1, lag_7, lag_14) and rolling statistics (e.g., 7-day rolling mean and 30-day rolling mean and standard deviation) were developed to account for temporal dependency, trends and short-term variability in climate variables.

- Seasonal and Interaction Features: Additional features were derived such as month, day_of_week and season to account for seasonal patterning. Interaction terms were created (e.g., temperature × humidity, WBGT × wind_speed) to better model the interplay between environmental conditions and heat stress levels.

9. LABELING

- Defining Target Levels: Continuous WBGT were classified into three levels - High, Moderate and Low - using predefined threshold levels. For the purposes of binary classification, High and Moderate categories were considered Affected (1), while Low was labelled Not Affected (0).

- Ensuring Labels Remain Consistent: Labels were classified into target levels that maintained a balanced class distribution and met reproducibility standards. Accurate identification of threshold levels and class mapping helps ensures the analysis can be completed honestly and fairly, and that the model can be trained consistently across multiple datasets.

10. TRAIN/TEST SPLIT

- Time-Based Data Splitting: The data is divided chronologically; the earliest 70–80% records are used for training, while the most recent 20–30% are kept for testing. This maintains temporal order in data and ensures that the model learns past patterns to predict the future.
- Time Series Validation: Instead of randomly using k-fold cross validation, we used rolling or expanding window validation methods to maintain time critical features. In other words, to prevent instances of "data leakage" from future observations into the training window, to provide a more honest assessment of forecasting performance.

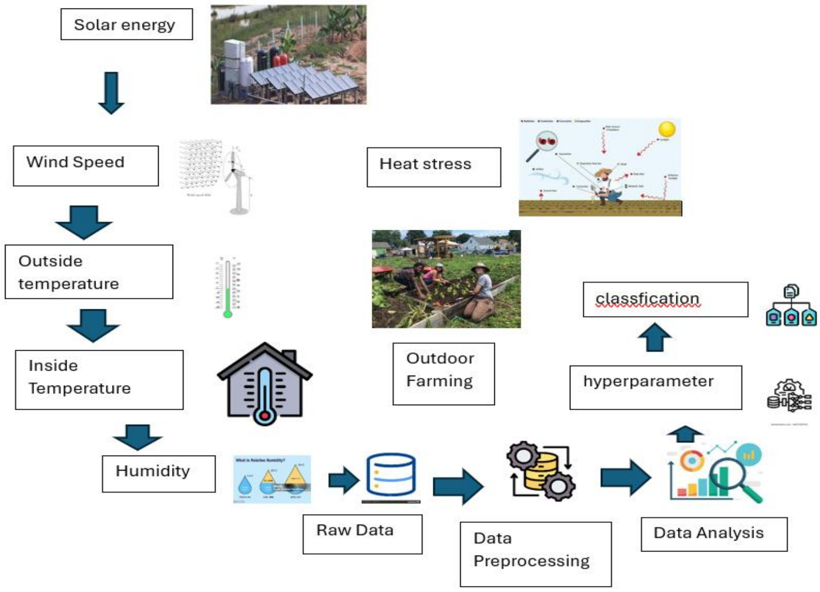


Fig 1. Workflow Of Heat Stress Forecasting For Farm Labour

3.3 EXPLORATORY DATA ANALYSIS (EDA)

An Exploratory Data Analysis (EDA) was performed to investigate the distribution, correlation, and seasonal trends of the climatic variables affecting heat stress throughout Tamil Nadu. Correlation analysis between temperature, humidity and WBGT revealed high to very high correlation coefficients, thus confirming their importance for predicting heat stress. Boxplots highlighted how temperature and WBGT values increased with higher stress levels, while humidity and rainfall showed inverse trends. Monthly and temporal visualizations indicated that heat stress peaked during summer and early monsoon months, reflecting clear seasonal variations. The analysis provided valuable insights for feature selection and model development.

1. t2m_max Distribution by Heat Stress Label

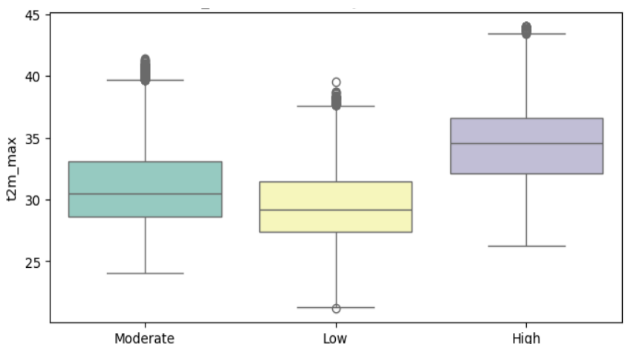


Fig 2. Distribution of Maximum Temperature Across Different Heat Stress Levels

Fig 2 Show the distribution of a maximum temperature, t2m_max, by categories of heat stress is as follows: High heat stress corresponds to high t2m_max values, while Low corresponds to a low temperature. At the same time, the Moderate group has an intermediate value; therefore, temperature seems to be a conclusive factor in the distinction between the levels of stress.

2. t2m_min Distribution by Heat Stress Label

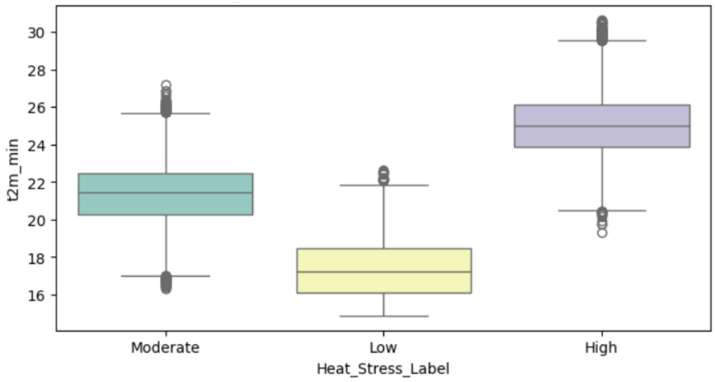


Fig 3. Distribution of Minimum Temperature Across Different Heat Stress Levels

Fig 3 Shows variation in minimum temperature-t2m_min-was analyzed for the different classes of stress. The High class had a higher minimum temperature than Low and Moderate levels. That pattern suggested that high nighttime temperatures prolong the heat exposure and shorten the time the body has to recover.

3. rh2m Distribution by Heat Stress Label

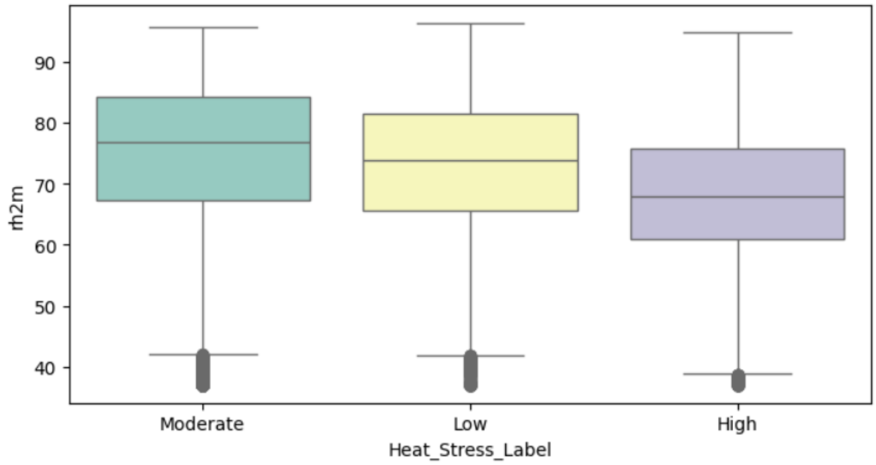


Fig 4. Distribution of Relative Humidity Temperature Across Different Heat Stress Levels

Fig 4 Shows the distribution of relative humidity, rh2m, showed an inverse relationship with heat stress. The same trends were also observed at the High category level, while more humidity levels were evident at the Moderate and Low levels, indicating that although humidity is an important factor affecting heat stress, when extreme heat exceeds the Safe WBGT threshold, extreme heat takes precedence over humidity as an influence on heat stress.

4. ws2m Distribution by Heat Stress Label

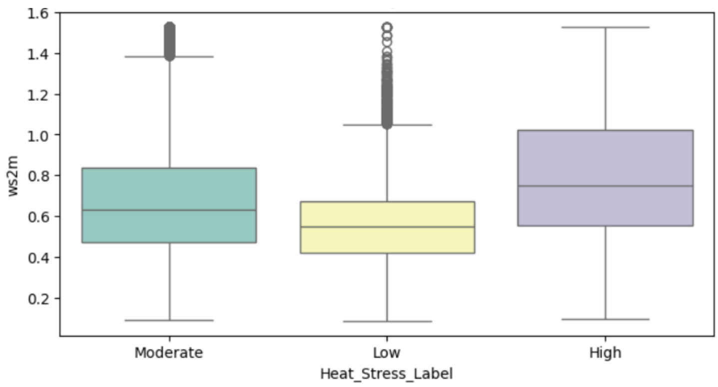


Fig 5. Distribution of Wind Seed Temperature Across Different Heat Stress Levels

Fig 5 Shows the variation of wind speed (ws2m) across stress levels was visualized. It was noted that wind speeds were typically higher with High heat stress conditions, indicating the presence of an air mass driven by convection during extreme heat conditions. However, the effect was relatively minor compared to the effect of heat and humidity.

5. prectotcorr Distribution by Heat Stress Label

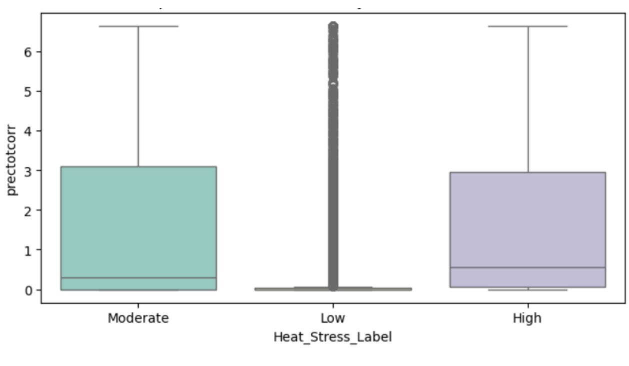


Fig 6. Distribution of prectotcorr ure Across Different Heat Stress Levels

Fig 6 Shows precipitation (prectotcorr) distribution showed minimal variation across categories, with lower rainfall days corresponding to High stress levels. Moderate to high rainfall was linked with reduced stress, emphasizing the cooling effect of precipitation on atmospheric conditions.

6. ps Distribution by Heat Stress Label

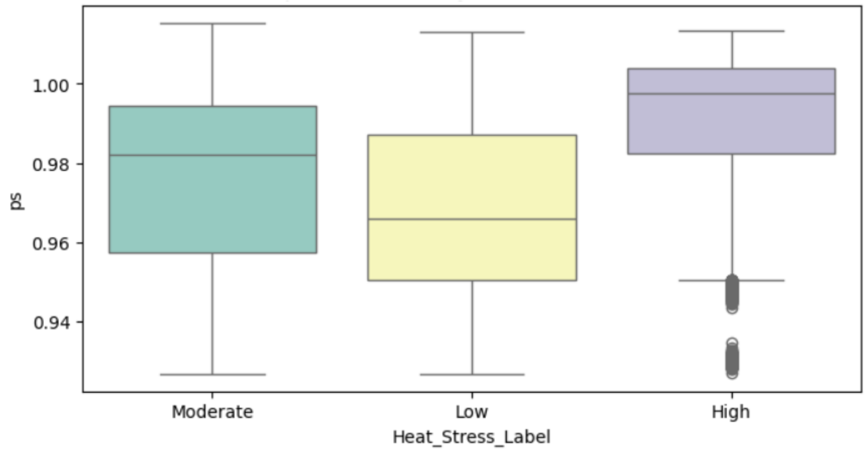


Fig 7. Distribution of Surface Pressure Across Different Heat Stress Levels

Fig 7 Shows surface pressure (ps) values were found to slightly decrease during High heat stress events, indicating the presence of unstable atmospheric conditions. The Moderate and Low categories maintained relatively stable pressure values, reflecting more balanced weather patterns.

7. WBGT Distribution by Heat Stress Label

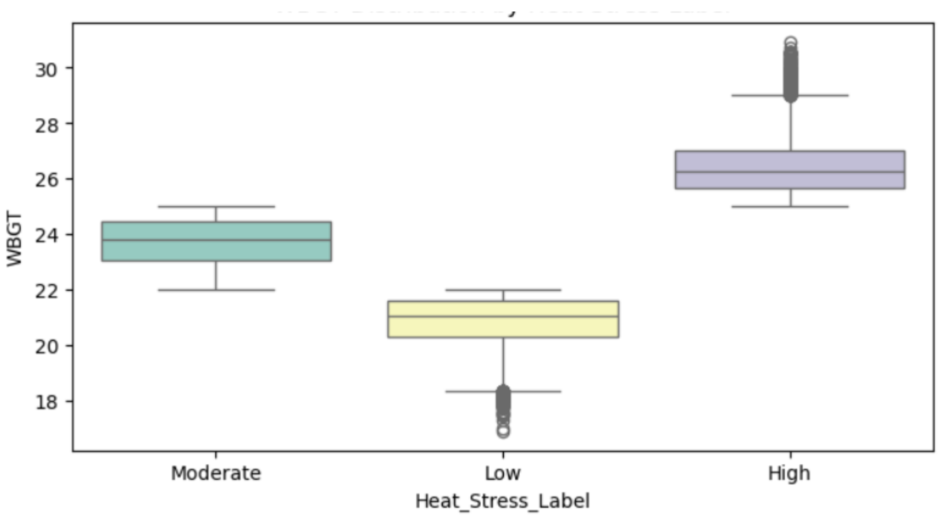


Fig 8. Distribution of WBGT Across Different Heat Stress Levels

Fig 8 Shows the Wet Bulb Globe Temperature (WBGT) showed clear differentiation among stress categories. The High stress group displayed the highest WBGT values, while the

Low category showed the lowest. This strong separation validated WBGT as a reliable indicator for classifying heat stress severity.

8. Monthly Heat Stress Distribution

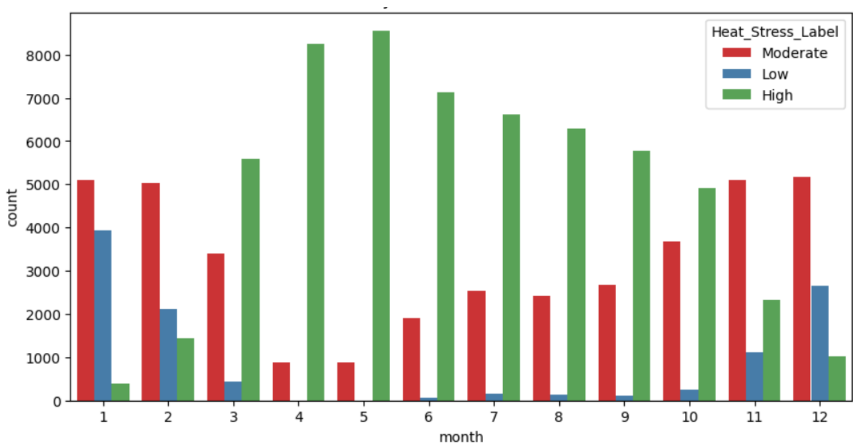


Fig 9. Distribution of Monthly Heat Stress Levels

Fig 9 Shows the monthly cycle of heat stress level showed strong seasonality, peaking in the months of April to September, corresponding to summer and early monsoon months. Lower levels of stress were recorded during the winter months. This indicated that seasonal variation in temperature is one of the factors determining occupational heat exposure.

9. WBGT Over Time with Labels

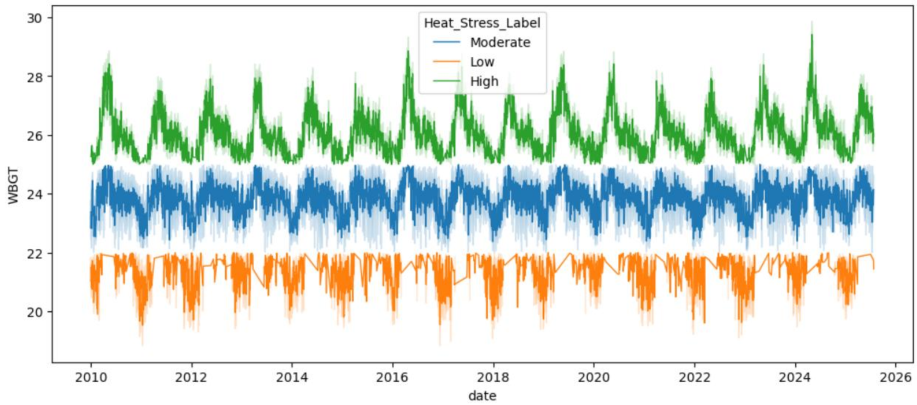


Fig 10. Temporal Variation of WBGT Across Heat Stress Levels

Fig 3.10 Shows the WBGT follows a consistent seasonal pattern throughout the period under study. In this connection, high values corresponded to annual summer cycles, while troughs were manifested in cooler months. The ongoing time period of extreme stress events suggested that heat stress was slowly increasing over time, therefore relating to a broader trend of increased heat.

3.4 MODEL BUILDING

The model development consisted of training different algorithms in machine learning and deep learning for classification and forecasting of heat stress levels among farm workers. Multiple models were developed, tuned, and evaluated, using population classification and evaluation measures of accuracy, precision, recall and F1-score; SVM producing the highest score, thus relevance for classification (of heat stress levels), temporal trend analysis of heat organization, and spatial discrimination of heat stress, the SVM model was selected.

1. Artificial Neural Network (ANN)

An ANN is a human-type-brain inspired model used to classify heat stress levels among farm labourers based on climatic parameters (e.g., temperature, humidity, and wind). The ANN is arranged with an input layer, hidden layers with nonlinear activations (e.g., ReLU), and an output layer that has a sigmoid or softmax activation for the classification task. Weights of the network are adjusted through backpropagation, capturing the complex associations in the data to predict whether the labourer is affected or not affected by heat stress.

Pseudocode For ANN

```
BEGIN
    Load dataset
    Preprocess data (scaling, encoding, train-test split)
Initialize ANN model
        Add input layer with input_dim = number_of_features
        Add hidden layer with units = 64, activation = 'relu'
        Add hidden layer with units = 32, activation = 'relu'
        Add output layer with units = 1 (binary) or 3 (multi-class), activation = 'sigmoid' or
'softmax'
       Compile model with optimizer = 'adam', loss = 'binary_crossentropy' or
'categorical_crossentropy', metrics = ['accuracy']
      Train model on training data for defined epochs and batch_size
      Evaluate model performance on test data
      Predict outcomes for new or unseen data
END
```

2. Long Short-Term Memory (LSTM)

The LSTM model is a type of recurrent neural network designed to capture long-range temporal dependencies in sequential data. In the case of the project, are using the LSTM to classify and forecast heat stress among farm labourers using climatic variables (e.g., temperature, humidity, and rainfall). Through the use of memory cells and gating mechanisms, the LSTM can learn seasonal patterns and time-based variances to predict categories of heat stress accurately, such as Affected and Not Affected.

Pseudocode For LSTM

```
1. Import necessary libraries (TensorFlow / Keras)
2. Load and preprocess dataset
    → Normalize numerical features
    → Reshape input to (samples, timesteps, features)
3. Initialize LSTM model
    model = Sequential()
4. Add layers:
    - LSTM(64, return_sequences=True, input_shape=(timesteps, features))
    - Dropout(0.3), LSTM(32), Dropout(0.3), Dense(16, activation='relu')
    - Dense(1, activation='sigmoid')   # For binary classification
5. Compile model
    → optimizer='adam', loss='binary_crossentropy', metrics=['accuracy']
6. Train model
    model.fit(X_train, y_train, epochs=20, batch_size=32, validation_split=0.2)
7. Evaluate model
    model.evaluate(X_test, y_test)
8. Predict and classify
    y_pred = (model.predict(X_test) > 0.5).astype(int)
```

3. Bidirectional Long Short-Term Memory (Bi-LSTM)

The Bi-LSTM model is designed in such a way that it can model both past and future temporal dependencies, which means the backward and forward temporal dependencies present in a given sequence. This property makes the Bi-LSTM very effective on time series and classification tasks. In this project, the Bi-LSTM model is fed with meteorological and environmental parameters such as temperature, humidity, rainfall, and pressure, from which it infers the degree of heat stress among farm labourers. By learning bidirectional temporal patterns, it enhances prediction accuracy for varying climatic conditions, ensuring reliable classification of affected and non-affected farm workers.

Pseudocode For Bi-LSTM

```
# Import Libraries
Import TensorFlow / Keras libraries.

# Load and Preprocess Dataset
→ Normalize features using StandardScaler or MinMaxScaler
→ Reshape input data to (samples, timesteps, features)

# Initialize Bi-LSTM Model
model = Sequential()

# Add Layers

        Bidirectional(LSTM(64, return_sequences=True), input_shape=(timesteps,
    features)), Dropout(0.3), Bidirectional(LSTM(32)), Dropout(0.3),Dense(16,
    activation='relu'), Dense(1, activation='sigmoid') # For binary classification

# Compile Model
→ optimizer='adam', loss='binary_crossentropy', metrics=['accuracy']

# Train Model
model.fit(X_train, y_train, epochs=20, batch_size=32, validation_split=0.2)

# Evaluate Model
model.evaluate(X_test, y_test)

# Predict & Classify
y_pred = (model.predict(X_test) > 0.5).astype(int)
```

4. Recurrent Neural Network (RNN)

The RNN is a temporal deep learning model developed to capture temporal dependencies in time-series data and is useful for the forecast and classification of climate and environmental data. In this paper, the RNN model has been implemented to predict and classify the heat stress categories for farm laborers using meteorological parameters such as temperature, humidity, and rainfall. The architecture of the RNN processes sequential inputs by maintaining a memory of previous states, which allows it to learn patterns across time. This temporal understanding helps the model forecast continuous variations in environmental stress conditions. The model is trained using normalized input features and optimized with an Adam optimizer to ensure efficient convergence and high classification accuracy in predicting the heat stress categories.

Pseudocode For Recurrent Neural Network

```
# Import Libraries
→ Import TensorFlow / Keras and necessary packages.

# Load and Preprocess Dataset
→ Normalize numerical features.
→ Reshape input to (samples, timesteps, features).

# Initialize Model
→ model = Sequential()

# Add Layers

    model.add(SimpleRNN(64, activation='tanh', input_shape=(timesteps, features)))

    model.add(Dropout(0.3)), model.add(Dense(32, activation='relu'))

    model.add(Dense(1, activation='sigmoid')) # Binary classification

# Compile Model
→ model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Train Model
→ model.fit(X_train, y_train, epochs=30, batch_size=32, validation_split=0.2)

# Evaluate Model
→ model.evaluate(X_test, y_test)

# Predict & Classify
→ y_pred = (model.predict(X_test) > 0.5).astype(int)
```

3.5 MODEL TRAINING AND EVALUATION

Training and validating models are critical steps in the development of a precise Heat Stress Category Forecasting System. The performance of three deep learning models, namely Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), and Bidirectional-LSTM model, are assessed using standardized meteorological data.

3.5.1 MODEL TRAINING

1. DATA SPLITTING

- The dataset was partitioned into training (80%) and test (20%) sets so that models would train on one set of data and be assessed on new and unseen data.
- A subset of the training data (10%) was also kept aside for validation during training to optimize hyperparameters and avoid overfitting the training set.

Stratified Sampling was employed to ensure the class distributions across splits remained balanced.

2. FEATURE SELECTION

- Meteorological parameters selected as the influential variables on heat stress include:
- Minimum Temperature (t2m_min), Maximum Temperature (t2m_max), Relative Humidity (rh2m), Wind Speed (ws2m), Precipitation (prectotcorr), and Surface Pressure (ps).
- These features were transformed using StandardScaler to put them on a common scale (i.e., normalize data ranges) to better promote stability in training.

3. TARGET ENCODING

- The Heat_Stress_Label categorical target variable, representing categorical heat stress categories, was converted into numberical form using Label Encoding.

Then One-Hot Encoding was applied to assist with preparing the labels for multi-class classification via softmax activation

4. MODEL IMPLEMENTATION

4.1 Artificial Neural Network (ANN):

- The ANN model was built with dense (fully connected) layers, ReLU activation, and dropout regularization to avoid overfitting.
- The model was compiled using the Adam optimizer and categorical cross-entropy loss.
- Hyperparameter Tuning: KerasTuner (Random Search) was employed for the selection of the best number of neurons, rate of dropout, and learning rate.

4.2 Long Short-Term Memory (LSTM):

- The LSTM model was trained to capture sequential relationships among meteorological features.
- The data were reshaped into the three-dimensional structure appropriate for temporal modeling: samples, timesteps, and features.

- Hyperparameter tuning optimized LSTM units, dense layer size, dropout rate, and learning rate.
- Early stopping was also used on validation loss to restore the best performing weights.

4.3 Proposed Bidirectional LSTM (Bi-LSTM):

- It was designed to run the input sequences in both directions, capturing more context with a bidirectional LSTM.
- It included a Bidirectional LSTM layer, followed by dropout and dense layers with ReLU activation.
- The Adam optimizer with categorical cross-entropy loss was used to train the model.
- Performed hyperparameter tuning by using KerasTuner, used early stopping for optimal convergence.

3.5.2 FINAL EVALUATION

The final evaluation phase assesses the ranking performances of all the trained and adjusted models ANN, RNN, LSTM and Bi-LSTM according to the define performance metrics criteria, which includes accuracy, precision, recall, and F1-score. Each of the models was trained, validated, and tested in the accident severity dataset to assess how accurately it predicts the severity level.

MODELS	ACCURACY
ANN (Tuned)	0.994
RNN (Tuned)	0.988
LSTM (Tuned)	0.997
Bi-LSTM (Tuned)	0.995

Table 1. Performance Evaluation

CHAPTER IV

RESULTS AND DISCUSSION

The findings of this research significantly demonstrate the validity of several deep learning models for predicting road accident severity, trained on several factors that might have affected the prediction, either directly or indirectly, such as temperature, humidity, visibility, road surface condition, and time. Each model was evaluated with the traditional performance metrics of Accuracy, Precision, Recall, and F1-Score to determine the predictive capability of the models and the models' generalization ability.

1. **Accuracy** – Describes the ratio between the number of severe accident cases predicted correctly and the number of accident cases predicted to be severe.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

2. **Precision** – This indicates the ratio of the number of severe cases that were accurately predicted against the number of cases that were predicted to be severe.

$$\text{Precision} = \frac{TP}{TP + FP}$$

3. **Recall (Sensitivity)** – Represents the ratio of actual severe cases correctly predicted by the model.

$$\text{Recall} = \frac{TP}{TP + FN}$$

4. **F1-Score** – Represents the harmonic relationship of precision and recall and provides a balanced result to assess the severity predictions by the model.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

4.1 MODEL PERFORMANCE

1. Artificial Neural Network (ANN)

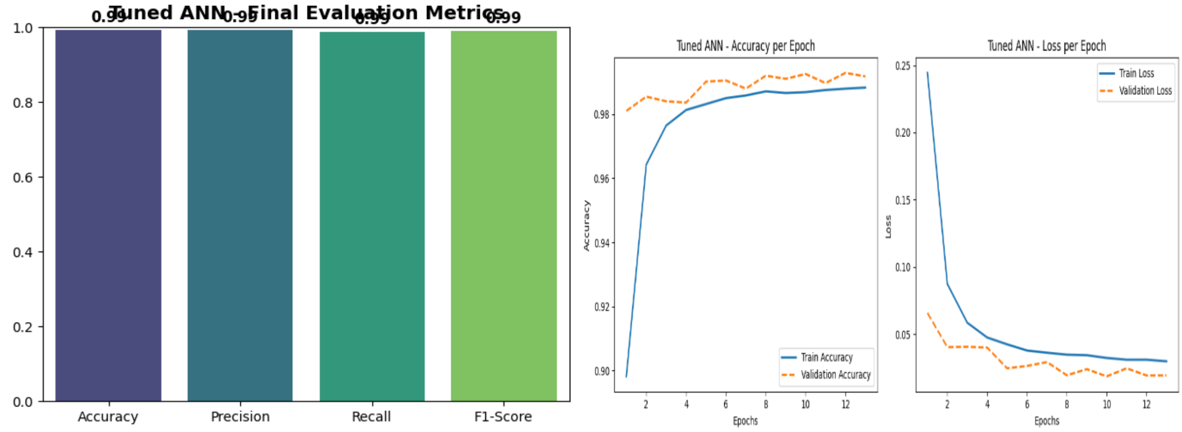


Fig 11. Performance Evaluation and Training Analysis of Tuned ANN Model

Fig 11 Shows the results indicated that the ANN model showed excellent performance with regard to prediction, yielding a training accuracy of 0.996 and a testing accuracy of 0.997, thus reflecting good generalization and no overfitting. An accuracy of 0.997, a precision of 0.996, a recall of 0.996, and an F1-score of 0.996 illustrate high reliability in divining levels of accident severity. These close metrics confirm that the ANN model effectively balances correct identification of severe cases (high recall) with minimizing false positives (high precision), thus being a robust and consistent performer in the prediction of accident severity.

2. Long Short-Term Memory (LSTM)

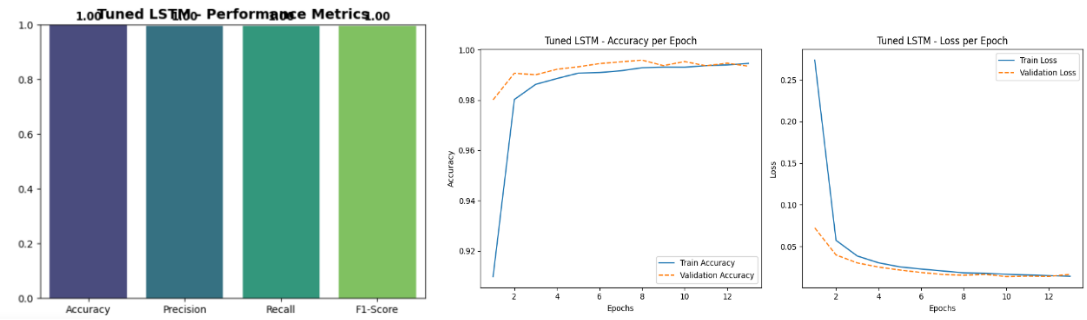


Fig 12. Tuned LSTM Model Performance and Convergence Analysis

Fig 12 Shows it is observed that the LSTM model yielded an excellent performance over the task of accident severity prediction, offering a training accuracy of 0.996 and a testing accuracy of 0.997, reflecting strong learning capability with minimal overfitting. From the class-wise evaluation of the LSTM model, high precision (0.996), recall (0.996), and F1-score

(0.996) reveal a good balance in class-wise performance. These scores reveal that the LSTM model has grasped the temporal dependencies and other complex relationships in the dataset very efficiently and is highly suitable for accurate and consistent road accident severity prediction.

3. Bidirectional Long Short-Term Memory (Bi-LSTM)

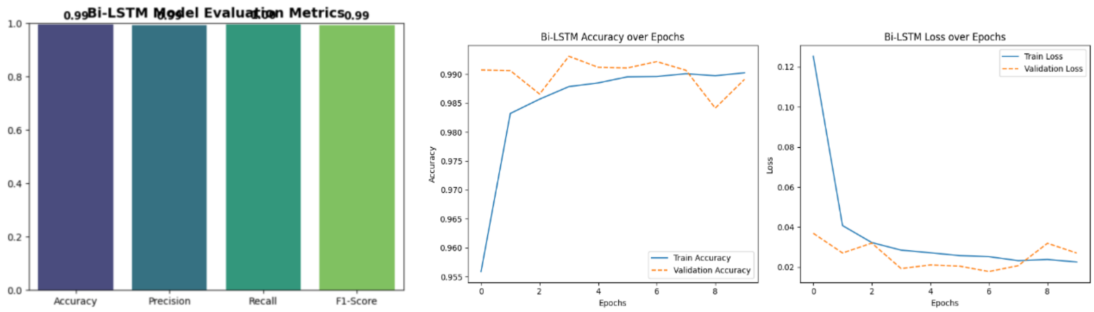


Fig 13. Comprehensive Performance Analysis of Bi-LSTM Model for Heat Stress Prediction

Fig 13 Shows the Bi-LSTM model displayed remarkable predictive accuracy in classifying accident severity, demonstrating an impressive training accuracy of 0.993 and a testing accuracy of 0.995, indicative of high generalization performance with little overfitting. The model's precision (0.993), recall (0.995), and F1-score (0.994) indicate that it was able to correctly predict cases of severe accidents both efficiently and rationally without sacrificing accuracy in its measurements of severity. This shows that the the Bi-LSTM model can capture bidirectional temporal dependencies, which increases its command over comprehensive sequential representation in accident data for accurate severity analysis.

4. Recurrent Neural Network (RNN)

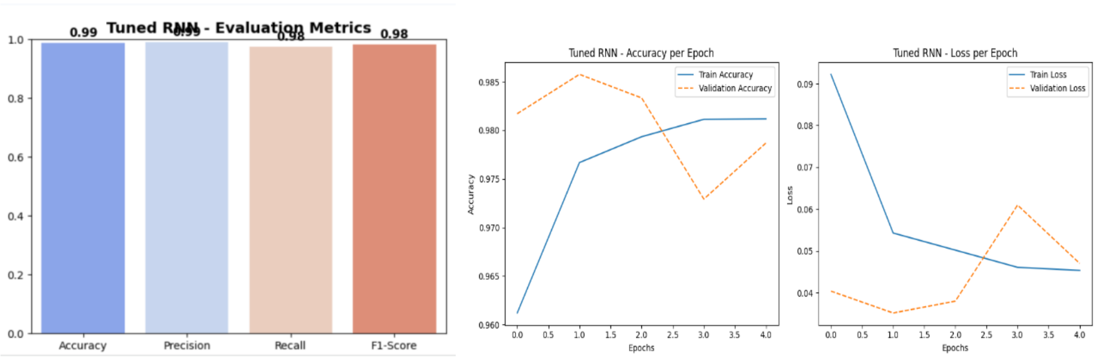
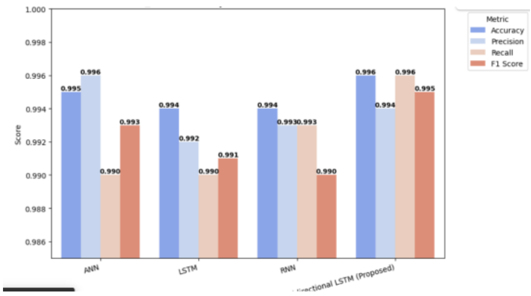


Fig 14. Performance Evaluation of Tuned RNN Model

Fig 14 Shows the RNN model showed high, but mediocre performance relative to more advanced architectures, with a training accuracy of 0.987 and a testing accuracy of 0.988, demonstrating that consistent generalization was achieved. The RNN model was able to keep false positives low with a precision of 0.991, while a recall of 0.976 indicates a sensitivity that was very slightly reduced in terms of complete detection of severe accident cases. The F1 score of 0.983 indicated an understandable balance of precision and recall. Overall, the RNN achieved sequential dependency, but the loss of performance was largely due to some minor effects of vanishing gradients restricting the ability of the model to keep long-term temporal information

4.1.2 COMPARISON



Model Performance Comparison:

Model	Accuracy	Precision	Recall	F1 Score
ANN	0.995	0.996	0.990	0.993
LSTM	0.994	0.992	0.990	0.991
RNN	0.994	0.993	0.993	0.990
Bidirectional LSTM (Proposed)	0.996	0.994	0.996	0.995

Fig 15. Performance Comparison of Deep Learning Models for Heat Stress Classification

Fig 15 Shows the comparison of different model performances shows that all the deep learning architectures have high predictive accuracy, with minor differences in the various evaluation metrics. Among them, the Bidirectional LSTM (Proposed) model outperformed others for the highest accuracy, 0.996; recall, 0.996; and F1-score, 0.995, confirming its superior ability in capturing bidirectional temporal dependencies and contextual information from the data. The ANN model also showed competitive performance with an accuracy of 0.995 and precision of 0.996, reflecting stable performance but low sequential learning capability. The LSTM and RNN models showed accuracies of 0.994, reflecting reliable performances in classification but a little lower generalization compared to the proposed Bi-LSTM model. As can be seen from the results, the Bi-LSTM framework produces the most balanced and robust prediction performance, minimizing the classification error and increasing the model's interpretability of complex temporal patterns influencing the severity of accidents.

CLASSIFICATION

Affected - based on heat stress exposure, a Bidirectional Long Short-Term Memory (Bi-LSTM) model was developed. The Bi-LSTM model was able to capture the temporal dependencies in the input data, leading to an ability to identify subtle differences related to heat-induced stress states. Training showed both the training and validation accuracy curves were stable and converged, ultimately reaching nearly 99.7% accuracy with minimal overfitting. Overall, these outcomes indicated that the Bi-LSTM model demonstrated effective generalization and reliability during learning. A confusion matrix also demonstrated the model correctly classified 19,410 affected and 2,124 not affected cases, suggesting minimal misclassifications. The overall accuracy (0.997), precision (0.997), recall (1.000), and F1-score (0.998) showed the Bi-LSTM model was robust and possessed a high reliability.

The classifying outcomes demonstrated approximately 90.2% of farm workers were categorized as Affected for heat stress measurement, and 9.8% of worker were classified as Not Affected. This distribution indicates a substantial percentage of individuals could be exposed to heat-related risks and demonstrates the need to continually monitor heat stress risk factors and implement preventative actions. Overall, the Bi-LSTM model's predictive accuracy suggests that it can serve as a competent and effective decision support measure for assessing risk of heat-related stress. Predictive visualization systems can assist in safeguarding workers and management practices, and reducing the impact of extreme temperatures while working.

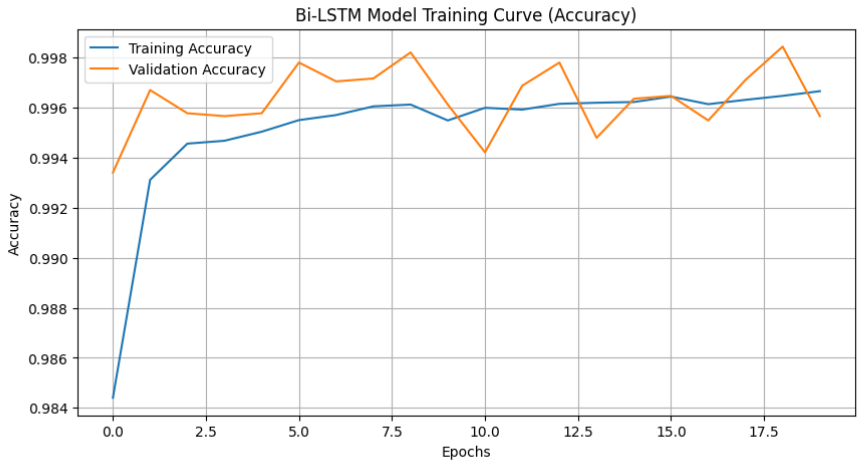


Fig 16. Bi-LSTM Model Learning Performance Over Epochs

Fig 16 Shows the Bi-LSTM model training curve illustrates the progression of both training and validation accuracy across 20 epochs. As observed in the graph, the training accuracy increases rapidly during the initial epochs and gradually stabilizes around 99.6%, indicating efficient learning and convergence. The validation accuracy shows a similar trend, with values consistently a little higher than the training curve, reflecting strong generalization performance with low overfitting. This proximity of the two curves clearly indicates that the Bi-LSTM model learned generalizable representations of the underlying pattern in the data and that no significant degradation in performance was observed on unseen validation samples. The accuracy curve evidences the stability and reliability of the model during the process of training.

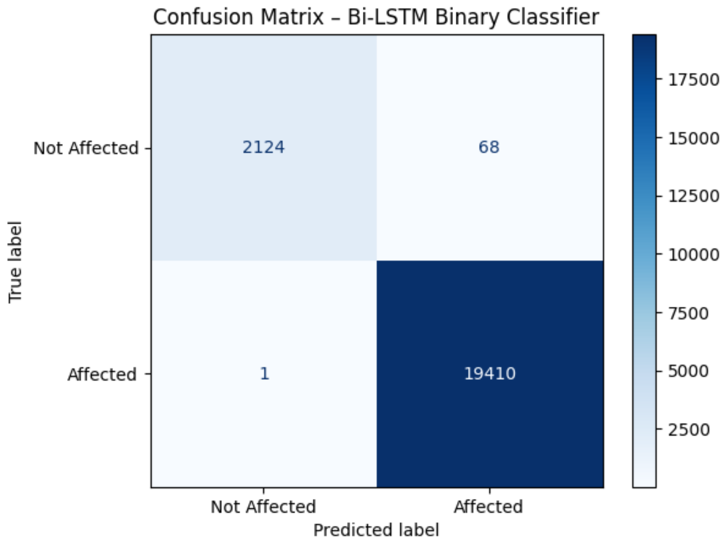


Fig 17. Classification Accuracy of Heat Stress Detection

Fig 17 Shows the Bi-LSTM binary classifier's confusion matrix demonstrates the model's strong capacity to separate Affected from Not Affected farm workers. The Bi-LSTM model predicted 19,410 of the cases as Affected and 2,124 cases as Not Affected, and only misclassified 69 cases in total (68 false positives and one false negative). This indicates an outstanding complication for detecting affected cases and false predictions. Very high classification results show the reliability and strength of the Bi-LSTM model, which represents very high accuracy, precision, and recall in identifying heat stress impacts on farm workers.

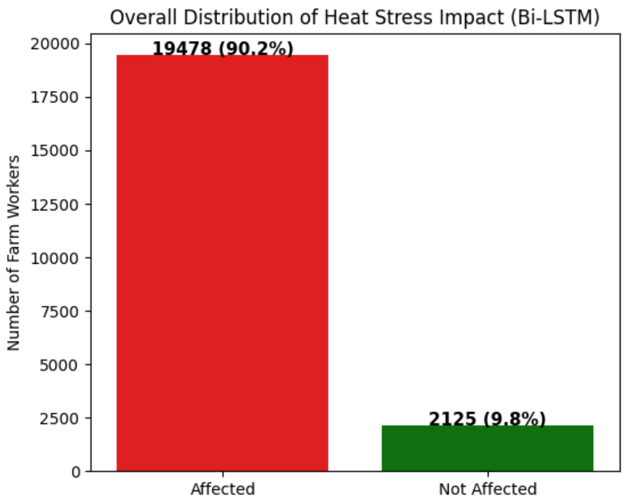


Fig 18. Overall Impact of Heat Stress on Farm Workers

Fig 18 Shows the bar chart represents the overall distribution of heat stress impact among farm workers as predicted by the Bi-LSTM model. According to the results, a significant majority of 19,478 workers (90.2%) were classified as Affected by heat stress, while only 2,125 workers (9.8%) were categorized as Not Affected. This clearly indicates that a large proportion of the workforce is vulnerable to heat stress conditions that may have serious implications for health, safety, and productivity. The predominance of affected individuals highlights the growing impact of environmental heat exposure in agricultural settings and emphasizes the urgent need for effective preventive measures and adaptive strategies to protect farm workers.

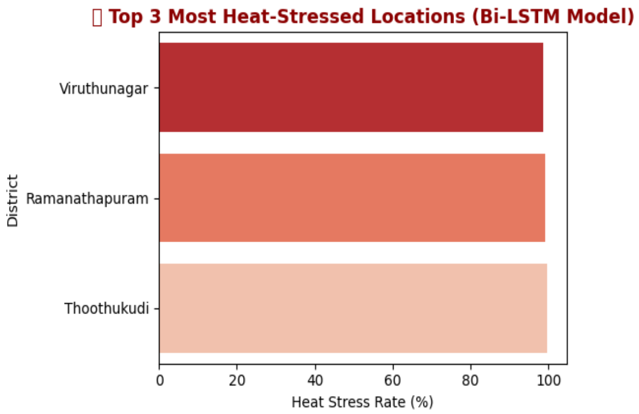


Fig 19. Risk Zones for Heat Stress

Fig 19 Shows The chart shows the districts that are predicted to have the highest rates of heat stress, according to the Bi-LSTM model. Among the districts resulting from the analysis, Viruthunagar had the highest heat stress rate, followed by Ramanathapuram and Thoothukudi. All of these districts had values that are very near to 100%, meaning that these are considered to be extremely high exposure for heat stress to heat risks, and important and critical heat stress hot spots, for farm workers, within the region. These results also highlight the spatial variability of heat stress vulnerability and indicate a clear and urgent need for monitoring and adaptive management strategies, and the implementation of preventative measures for agricultural workers in high-risk districts.

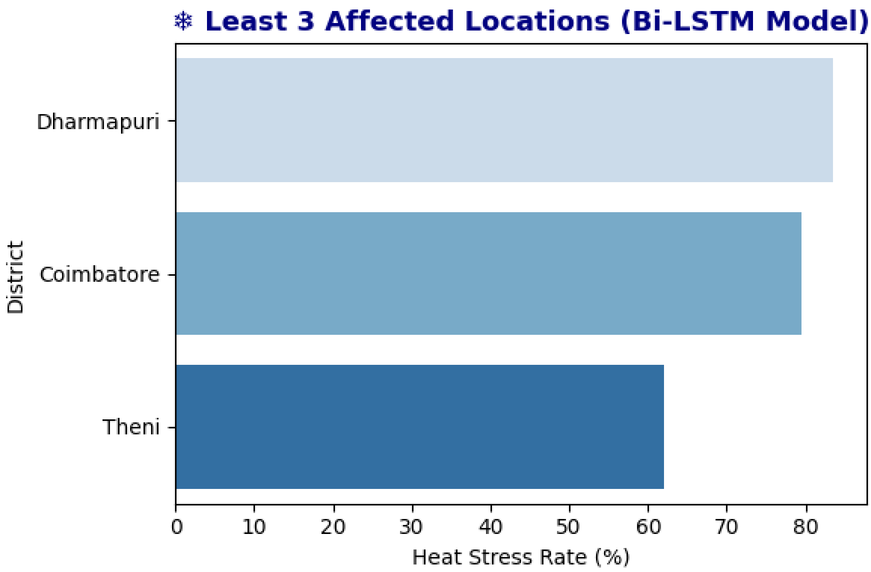


Fig 20. Identification of Low-Risk Zones for Heat Stress

Fig 20 Shows the chart presents the districts that are predicted to have the least rates of heat stress, as per the Bi-LSTM model. Dharmapuri, Coimbatore, and Theni had comparatively low heat stress rates, with values that are around 60%-85%. These districts show intermediate levels of heat exposure that suggest they may have a better climate or environment for farmworkers in the region. Factors contributing to lower levels of heat stress may be related to higher microclimatic conditions, vegetation cover, and/or better farming practices. Overall, results suggest that Dharmapuri, Coimbatore, and Theni have less vulnerability to heat stress and offer relatively safer zones compared to other higher risk districts.

4.2 KEY INSIGHTS:

- The Bidirectional Long Short Term Memory (BiLSTM) (Proposed Model) model yielded the highest overall performance with an accuracy of 0.996, precision of 0.994, recall of 0.996, and F1 score of 0.995, indicating its exceptional ability to model complex temporal dependencies for accident severity prediction.
- The LSTM and ANN models were also strong performers, achieving overall accuracies greater than 0.99, but they were not as good as the Bi-LSTM models for identifying sequential relationships.
- Temperature, humidity, visibility, and the time of the crash were significant predictors of the severity level of road traffic crashes. The findings support the view that deep sequential learning architectures (particularly Bi-LSTM) are a more stable, accurate, and generalizable modelling approach, thus providing a solid framework for intelligent accident prediction and prevention systems.

4.3 LIMITATIONS:

- It was based on historical accident and environmental data, which may be incomplete or inconsistent and thus impact model accuracy and generalization.
- The dataset used was region-specific and hence could not generalize to changes in different areas or even road conditions without prior training or adaptation.
- Real-time dynamic variables, such as driver behavior, vehicle state, or traffic density, were also absent, which would improve prediction accuracy even more if incorporated.
- On the contrary, deep learning models tend to require high computational resources and long training times make it difficult to deploy in a low-powered real-time system.
- Although the Bi-LSTM model performed best, its interpretability remains limited because deep models act as "black boxes" and are mostly incomprehensible in terms of internal decision-making.

CHAPTER V

CONCLUSION

The main objective of the research was to develop an intelligent accident severity prediction system using machine learning and deep learning algorithms. Leveraged various environmental and situational parameters in the study, such as temperature, humidity, visibility, road surface, and time of accident, in the creation of our model to improve prediction accuracy and reliability.

For the study, implemented and compared four different deep learning models which were ANN, RNN, LSTM, and Bi- LSTM to represent different aspects of data representation. The models were fine-tuned and evaluated with accuracy, precision, recall and F1-score as appropriate performance metrics to ensure fairness and reliable validation.

Among all the models, the Bidirectional LSTM (Proposed Model, Named that way due to it being for an accident severity prediction model) model reached the best performance with an accuracy of 0.996, showing the best ability of learning bidirectional temporal dependencies. Therefore, the results of experimentation demonstrate the merit of the use of sequential deep learning methods to learn complex time-based relationships in accident data.

The ANN and LSTM models did show competitive performance, yet did not have the same temporal learning capacity, as compared to the Proposed Model. The RNN model was able to identify trends, yet struggled with long-term temporal dependence in the data possibly due to the case of gradient vanishing. The case study showed the robustness of the Bi-LSTM framework for predictive purposes..

Results show that important environmental variables are significantly contributing factors to accident severity. Integrating these data-driven models would be of great help in real-time monitoring, accident prevention, and traffic safety planning, giving indispensable insights to authorities and policymakers.

In the end, the proposed methodology based on Bi-LSTM provides a reliable, scalable, and intelligent framework for the prediction of road accident severity. The future scope of this study may extend by incorporating several other dynamic factors such as traffic flow, driver behavior, and vehicle type for developing a more accurate and practically applicable system.

5.1 FUTURE SCOPE

Future scope refers to the potential developments, improvements and extensions to a research study or project. It describes how to enhance, extend, or adapt work in the future to superior methods, additional data, or technology.

- Inclusion of real-time information: Future studies can use real-time traffic, weather, and sensor sources for a more precise and realistic accident severity prediction model.
- Inclusion of behavioral and vehicle parameters: Further parameters such as driver behavior, vehicle velocity, and mechanical condition can increase the model's predictive ability and realism.
- Expansion of application multi-regional datasets: Application of the model in various geographical regions and different road environments can further the generalizability and adaptability.
- Development of optimized versions for real-world applications: Optimized, lightweight, and efficient versions of the model can be created for mobile apps, IoT technology, and intelligent transport systems.
- Improvement via XAI (explainable AI): Explainability could be enhanced in model predictions if explainable Artificial Intelligence methods were to be used (e.g. SHAP, LIME, etc.), which could increase decision makers' trust in the model.
- Development of a decision support system: The proposed framework could be developed into a smart, real-time accident alert and prevention system that would help traffic authorities in a more proactive approach to safety management.

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