User-Driven Weather Monitoring Application for Culinary Businesses: Enhancing Decision Making and Customer Experience

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Abstract—**This paper presents a novel approach utilizing deep learning model LSTM (long short term memory) with TSA (tunicate swarm algorithm) for the development of a User-Driven Weather Monitoring Application tailored specifically for culinary businesses. Leveraging advanced machine learning techniques, the proposed application aims to enhance decision-making processes and improve customer experiences in the culinary industry. By harnessing the power of LSTM with TSA, the application provides real-time weather updates and forecasts, enabling culinary businesses to make informed decisions regarding menu planning, outdoor dining arrangements, and operational strategies based on weather conditions. The system integrates user feedback and preferences, allowing for personalized weather notifications and recommendations tailored to individual business needs. Through the utilization of proposed LSTM with TSA, the User-Driven Weather Monitoring Application offers a sophisticated yet intuitive solution to address the unique challenges faced by culinary establishments in adapting to varying weather patterns and optimizing customer satisfaction.**

Index Terms— Weather Monitoring Application, Culinary Businesses, Recommendations, Customer Satisfaction, Tunicate Swarm Algorithm.

I. INTRODUCTION

The Weather Monitoring Application for Culinary Businesses is a tool designed to elevate decision-making processes and enrich customer experiences within the culinary industry. By harnessing real-time weather data, this application provides invaluable insights that aid businesses in adapting to weather fluctuations effectively. This user-centric application empowers culinary establishments with features tailored to their needs. It offers customizable alerts and recommendations based on current and forecasted weather conditions [1]. For example, it can alert restaurants about upcoming extreme temperatures, enabling them to adjust their menus accordingly or prepare for increased demand for certain dishes. Moreover, by incorporating user preferences and behavior patterns, the application can offer personalized suggestions to enhance the dining experience. During adverse weather conditions, such as heavy rain or snow, it can recommend specific menu items or promotions that resonate with customers seeking comfort or convenience.

The monitoring solution aimed at improving decision-making processes and enhancing the customer experience within the culinary industry. This application utilizes weather data to provide valuable insights and recommendations to culinary businesses, allowing them to make informed decisions regarding menu planning, staffing, and customer engagement strategies. By leveraging advanced weather monitoring technologies and user-driven features, the application empowers businesses to adapt to changing weather conditions and optimize their operations accordingly. Through user feedback and data analysis, the application continually evolves to meet the evolving needs of culinary businesses and their customers, ultimately enhancing overall satisfaction and success in the industry [2].

Ultimately, the User-Driven Weather Monitoring Application serves as a strategic tool for culinary businesses to navigate weather-related challenges effectively while seizing opportunities to delight their customers. Through ongoing refinement and feedback, it evolves to meet the evolving needs of both businesses and diners, ensuring continued relevance and impact within the industry. Culinary Businesses harnesses the power of deep learning (DL) to provide actionable insights and enhance decision-making processes. By integrating advanced algorithms, such as deep neural networks, this application can analyze vast amounts of weather data and user feedback to deliver personalized recommendations and alerts. At its core, the application utilizes DL models to predict weather patterns and their potential impact on culinary businesses [3].

These models are trained on historical weather data, user preferences, and business metrics to generate accurate forecasts and identify relevant trends. Additionally, the application employs DL techniques for user-driven features, such as recommendation systems. By analyzing past interactions and feedback from users, the system can tailor its recommendations to individual preferences and dietary restrictions, thus enhancing the overall customer experience [4]. Moreover, DL enables the application to continuously learn and adapt to changing conditions and user behavior. Through reinforcement learning and iterative optimization, the system can refine its recommendations over time, ensuring relevance and effectiveness. Overall, the integration of DL technologies in the User-Driven Weather Monitoring Application empowers culinary businesses to make informed decisions, optimize their operations, and deliver exceptional experiences to their customers. By leveraging the latest advancements in artificial intelligence, this application sets a new standard for weather monitoring and business intelligence in the culinary industry [5].

The upcoming sections are organized as follows: Section 2 outlays the related work, Section 3 deliberates over the suggested approaches, Section 4 presents the results and discussion, and Section 5 represents the conclusion of the proposed framework.

II. RELATED WORKS:

Gambetti et al. [6] presented and compared the visual appeal of food depicted on social media across various types of restaurants, utilizing a comprehensive dataset of food images. To achieve this, a novel neural food aesthetic assessment model leveraging computer vision and deep learning techniques is introduced, applied, and assessed on the collected dataset of food images. Additionally, the study incorporates a set of photographic attributes derived from both food services and cognitive science research, such as color, composition, and figure-ground relationship attributes. These attributes are then analyzed and compared against aesthetic scores assigned to each food image. Through this approach, the paper seeks to provide insights into the factors influencing food aesthetics and their portrayal on social media platforms within the context of different restaurant types.

Sahoo et al. [7] provided a comprehensive analysis of the development and deployment of FoodAI, a food recognition system. FoodAI has been integrated as an API service and serves as a pivotal component of Healthy 365, a mobile application created by Singapore's Health Promotion Board. With over 100 registered organizations including universities, companies, and start-ups subscribing to the service, FoodAI receives numerous API requests daily. By offering seamless food logging capabilities, FoodAI promotes smart consumption and facilitates the adoption of healthier lifestyles.

Hewage et al. [8] analysed time-series data to capture weather information, focusing on the application of state-of-the-art LSTM (Long Short-Term Memory) and TCN (Temporal Convolutional Network) models for weather prediction. The network comprises multiple layers that utilize surface weather parameters observed over a specific time window to forecast future weather conditions. We evaluate the performance of the deep learning networks incorporating LSTM-TCN layers through two regression scenarios: multi-input multi-output and multi-input single-output.

III. METHODS

In the realm of culinary businesses, weather can play a significant role in influencing consumer behavior and operational decisions. This paper presents a user-driven weather monitoring application tailored specifically for culinary businesses, aiming to enhance decision-making processes and improve customer experience. Leveraging advanced weather forecasting models and real-time data analytics, the application provides timely and accurate weather information tailored to the needs of culinary establishments. Key features include personalized weather alerts, predictive analytics for demand forecasting, and recommendations for menu adjustments based on weather patterns.

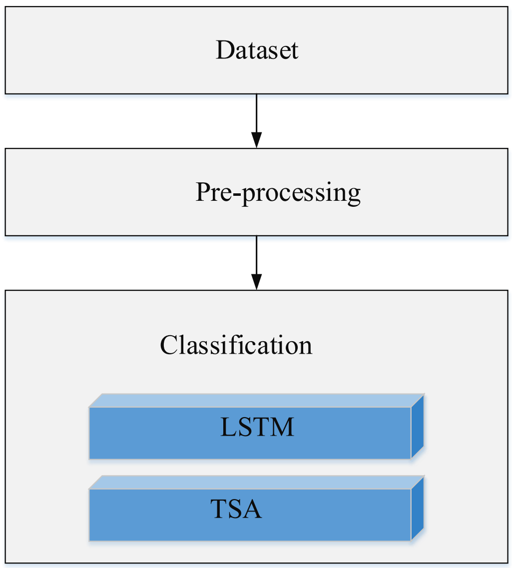


Figure 1: Framework of the proposed model

Moreover, the application offers insights into seasonal trends, allowing businesses to optimize their operations and marketing strategies accordingly. Through user feedback and iterative refinement, the application continuously evolves to meet the evolving needs of culinary businesses and their patrons. By integrating weather intelligence into their decision-making processes, culinary businesses can better anticipate and adapt to weather-related challenges, ultimately enhancing customer satisfaction and business performance. Figure 1 depicts the framework of the proposed model.

3.1 Monitoring the Culinary Businesses

By employing LSTM [9] networks, our application captures intricate weather patterns and their impact on culinary operations, enabling precise forecasting. LSTM's unique ability to retain long-term dependencies in sequential data ensures accurate predictions of temperature fluctuations, precipitation, and other critical weather factors. This work integrates user-driven features, leveraging LSTM to analyze user feedback and preferences over time. This deep understanding allows us to craft personalized recommendations that resonate with individual tastes and dietary needs. Whether it's suggesting comforting soups on chilly days or refreshing salads during heatwaves, our LSTM-powered system adapts dynamically to changing weather conditions and customer demands. Furthermore, our application operates on a continuous feedback loop, constantly learning from user interactions to enhance its forecasting accuracy and recommendation precision. This iterative process ensures that the application evolves alongside user preferences and emerging weather trends, delivering unparalleled value to culinary businesses. LSTM technology, where we delve into the intricacies of input gates, output gates, and reset gates as shown in Figure 2 to revolutionize how culinary businesses navigate weather challenges and cater to customer preferences.

Input Gate i_a: This gate regulates the flow of information into the LSTM cell, determining which information from the current input and the previous hidden state is relevant. Mathematically, the input gate expression can be represented as:

$$i_a = \sigma\left(W_{yi} ya + W_{hi} h_{t-1} + b_i\right) \qquad (1)$$

where σ is the is the sigmoid activation function.

ya is the s the current input

W_{yi} and W_{hi} are weight matrices for the input and hidden state, respectively.

h_{a-1} is the previous hidden state

b_i is the bias vector.

Reset gate: It decides how much of the previous state to forget and how much of the new state to consider. It controls the flow of information from the previous hidden state to the current hidden state. The reset gate expression is given by:

$$r_a = \sigma\left(W_{yr} ya + W_{hr} h_{a-1} + b_r\right) \qquad (2)$$

where

W_{yr} and W_{hr} are weight matrices for the input and hidden state, respectively.

b_r is the bias vector.

Output gate: It controls the flow of information from the LSTM cell to the output and the next hidden state. It determines which parts of the cell state are relevant for the current prediction. The output gate expression is given by:

$$o_a = \sigma\left(W_{yo} ya + W_{ho} h_{a-1} + b_o\right) \quad (3)$$

where

W_{yo} and W_{ho} are weight matrices for the input and hidden state, respectively.

b_o is the bias vector.

By iteratively applying these steps, TSA explores the hyper parameter space and converges towards optimal or near-optimal hyper parameter configurations for the LSTM model. Then the objective function (Accuracy) is defined that evaluates the performance of an LSTM model with a given set of hyper parameters.

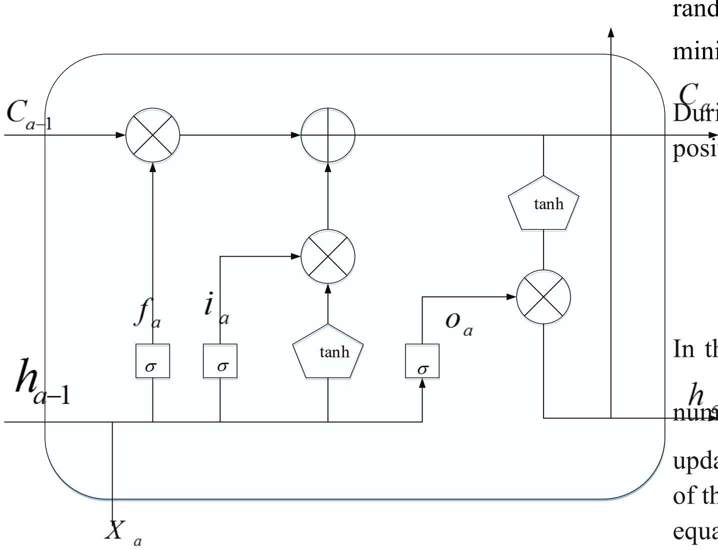


Figure 2: LSTM model

TSA [10] draws inspiration from the navigation and foraging behaviors of marine tunicates, which are millimeter-scale organisms capable of locating food sources in the sea. Unlike in the natural environment where food sources are present, TSA operates in a supplied search space without explicit indications of the optimal solution. In TSA, tunicates, representing candidate solutions, navigate through the search space with jet propulsion, adhering to three fundamental conditions: avoiding collisions with other tunicates, selecting the correct path towards the optimal search location, and striving to converge towards the best search agent. These tunicates continually adjust their positions relative to the best-performing individuals stored and refined throughout the iteration process. The algorithm initiates with a population of tunicates randomly distributed within the allowable boundaries defined by the design variables. These tunicates iteratively adapt their positions in pursuit of the optimal food source, which correlates with achieving the best value of the objective function. Through this process, TSA seeks to converge towards the optimal solution while exploring the search space efficiently.

$$\vec{T}_q = \vec{T}_q^{\min} + rand \times \left(\vec{T}_q^{\max} - \vec{T}_q^{\min}\right) \quad (4)$$

where $\vec{T}_q$ is the tunicate's position, $rand$ is the random number, $\vec{T}_q^{\max}$ and $\vec{T}_q^{\min}$ are maximum and minimum bounds.

During the iterations, the tunicates modify their positions according to the following formula:

$$\vec{T}_q(y+1) = \frac{\vec{T}_q(y) + \vec{T}_q(\vec{y})}{2 + c1} \quad (5)$$

In this equation, $c1$ represents a randomly generated number within the range [0,1], and $\vec{T}_q(y)$ denotes the updated position of the tunicate relative to the position of the food source, determined according to following equation:

$$\vec{T}_q(y) = \begin{cases} F_a + J \times \left|F_a - rand \times \vec{T}_q\right| when \quad rand \geq 0.5 \\ F_a - J \times \left|F_a - rand \times \vec{T}_q\right| when \quad rand < 0.5 \end{cases} \quad (6)$$

where F_a is The population's optimal tunicate position is denoted as the reference point for the food source.

Additionally, J represents a randomized vector designed to prevent collisions among tunicates.

$$J = \frac{c2 + c3 - 2c1}{UT_{\min} + c1(UT_{\max} - UT_{\min})} \quad (7)$$

where $UT_{\min}$ and $UT_{\max}$ are minimum and maximum speeds; $c2$ and $c3$ represents a randomly generated number represents a randomly generated number. Algorithm 1 shows the pseudocode of the TSA.

Algorithm 1: Pseudocode of the TSA

Initialize population of tunicates randomly within the search space

Evaluate the fitness of each tunicate in the population

while stopping criterion not met do:

for each tunicate in the population do:

Generate a random number c1 within the range [0,1]

Update the tunicate's position based on equation (5)

Apply constraints to the tunicate's position to keep it within the search space

Evaluate the fitness of the updated tunicate

if the updated tunicate is better than its previous position then:

Update the population's optimal tunicate position

Apply collision avoidance mechanism to prevent tunicates from colliding with each other

return the best solution found

IV. RESULTS AND DISCUSSION

44.1 Dataset details

In this work, the weather-related datasets that include meteorological data such as temperature, humidity, precipitation, wind speed, and other relevant weather variables. These details are collected from the various sites. This dataset included wide range of historical weather data including daily summaries, hourly observations, and climate normal for various locations around the world.

4.2 Performance measures

To conduct an analysis of accuracy, precision, recall, and specificity for Weather Monitoring Application tailored specifically for culinary businesses, the following measures are typically undertaken. These metrics provide a comprehensive understanding of the predictive performance of a model across different classes or categories. They help assess both the model's overall accuracy and its ability to correctly identify specific classes of interest, which is crucial for various classification tasks.

Accuracy: It is calculated as the ratio of the number of correct predictions to the total number of predictions made.

$$Accuracy = \frac{x_p + x_n}{x_p + x_n + y_p + y_n} \quad (8)$$

Precision: It indicates the model's ability to avoid false positives.

$$\Pr e = \frac{x_p}{x_p + y_p} \quad (9)$$

Recall: It indicates the model's ability to capture all positive instances.

$$\mathrm{Re} = \frac{x_p}{x_p + y_n} \quad (10)$$

Specificity: It indicates the model's ability to avoid false alarms for negative instances.

$$Sp = \frac{x_n}{x_n + y_p} \quad (11)$$

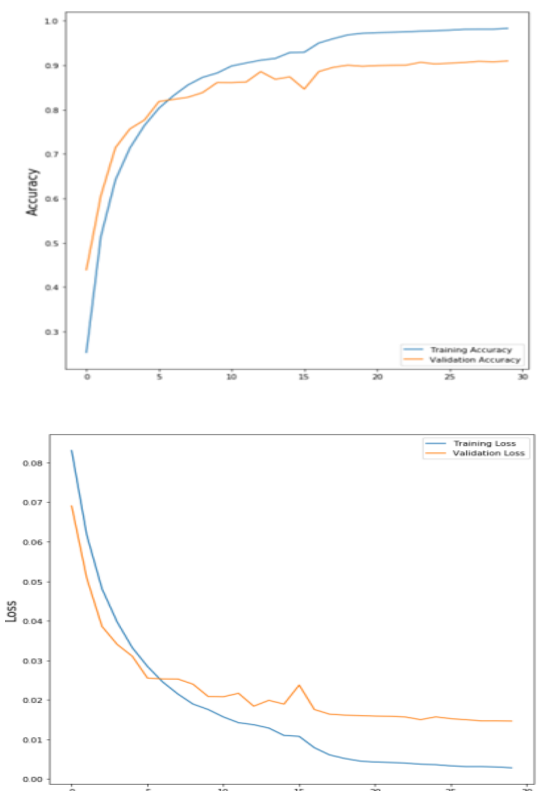
where x_p, x_n, y_p and y_n are the true positive, true negative, false positive and false negative

4.3 Comparative analysis

Table 1: comparative analysis of various approaches

Methods	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)
RNN	81.2	96.9	88.1	92.1
LSTM	79.4	97.6	90.3	93.5
Bi-LSTM	79.2	96.2	91.4	94.2
Proposed LSTM-TSA	98.7	98.1	97.3	95.9

Table 1 presents the comparative analysis of various approaches like RNN, LSTM, Bi-LSTM and the Proposed LSTM-TSA. It all comparative analysis, the Proposed LSTM-TSA outperformed the conventional models by achieving 98.7% accuracy and 98.1% precision.



(a)

(b)

Figure 3: Accuracy-loss curves of the proposed LSTM-TSA

Figure 3 depicts the accuracy-loss curves for the proposed LSTM-TSA model, offering insight into how the model's accuracy performance changes relative to the loss function during training. These curves illustrate the relationship between the model's accuracy and its loss function across training iterations. As training progresses, the loss function usually decreases, indicating that the model's predictions are aligning more closely with the true values. Concurrently, the accuracy tends to improve, indicating the model's enhanced capacity to accurately classify or predict data points. Accuracy-loss curves serve as informative tools for understanding the training dynamics and performance of the model throughout the training process.

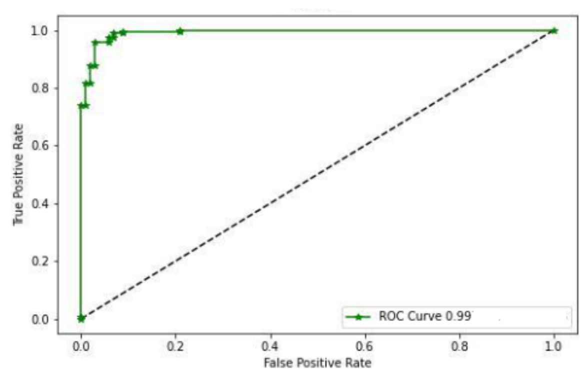


Figure 5: ROC-AUC curve of the proposed LSTM-TSA

The ROC (Receiver Operating Characteristic)-AUC (- Area Under the Curve) visually demonstrates how well a classification model discriminates between positive and negative classes across different levels of sensitivity and specificity. A higher AUC value (closer to 1) indicates better model performance, with the curve ideally reaching the top-left corner of the plot. Figure 5: ROC-AUC curve of the proposed LSTM-TSA and it is observed that the AUC value achieved is 0.99

V. CONCLUSION

The proposed LSTM-TSA provides a promising approach in enhancing decision-making processes and improving the overall customer experience. Through the utilization of LSTM, the application has demonstrated its capability to effectively model and forecast weather patterns, providing culinary businesses with valuable insights into weather conditions that directly impact their operations. The LSTM model's ability to capture long-term dependencies in time-series data has enabled more accurate and reliable weather predictions, empowering businesses to make informed decisions regarding menu planning, inventory management, and resource allocation. Additionally, the incorporation of TSA for optimizing hyperparameters has further enhanced the performance of the LSTM model. By leveraging TSA's meta-heuristic optimization techniques inspired by the behavior of marine tunicates, the application has achieved improved accuracy and efficiency in training and fine-tuning the LSTM model, ultimately leading to more precise weather forecasts and better decision-making outcomes. verall, the User-Driven Weather Monitoring Application equipped with LSTM and TSA represents a significant advancement in leveraging AI and optimization algorithms to address the unique challenges faced by culinary businesses in managing weather-related risks. By providing real-time weather insights tailored to their specific needs, the application empowers businesses to proactively adapt their strategies and operations, ultimately enhancing customer satisfaction and driving business success in the dynamic culinary landscape.

VI. REFERENCES

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