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Predicting and Analyzing Human Daily Routine Using Machine Learning

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Abstract **- Increasing productivity hinges on motivation, yet often individuals inadvertently lose productivity due to health issues and inefficient time management. In the tech domain, various wearable devices like watches, belts, and cameras have emerged to monitor and offer productivity recommendations. However, contemporary society calls for a more intelligent solution - a single mobile application capable of behavior monitoring without external devices. This research delves into such a solution, aiming to comprehend and predict daily human routines via a mobile app, eliminating the need for wearables. The central focus encompasses the detection of sleep patterns, location tracking, food consumption monitoring, and emotion tracking. The ultimate goal is to understand and forecast these facets of user behavior and evaluate their impact on productivity. Leveraging mobile phone sensors for data collection obviates the need for additional hardware. The accumulated data feeds into machine learning models to predict routines. The study's outcomes aspire to provide insights into individual daily behaviors and empower the application to encourage users to make adjustments that bolster productivity. This research contributes to the field by harnessing smartphone technology to enhance users' understanding of their behaviors and optimize their daily routines.**

Keywords: productivity, daily routine predictor, machine learning, non-wearable monitor, mobile application.

I. INTRODUCTION

As human beings, each person follows a distinct daily routine. However, what sets individuals apart is the degree of understanding they have about their life patterns. Undoubtedly, the daily routines of people hold immense significance, serving as a pivotal factor in determining their path towards success or otherwise. Consequently, cultivating a profound comprehension of our daily routines becomes imperative for fostering an efficient and productive lifestyle. The analysis of human daily routines extends its implications across diverse domains, including sociology, psychology, and computer interactions.

The prediction and analysis of human daily routines offer a multitude of avenues, encompassing the use of various tools such as sensors, wearable devices, smartwatches, smartphones, and third-party APIs. To truly grasp an individual's daily monotony, a comprehensive spectrum of data needs to be gathered, including factors like voice, location, social interactions, videos, age, personality type, and communication patterns. Leveraging Machine Learning (ML) algorithms, there are numerous approaches to analyze and understand the routine patterns of people. The identification and analysis of these patterns, as well as the ability to predict routine activities, hold profound significance and utility. Much of the prior research and existing systems have been rooted in the exploration of human daily routines, with a heavy emphasis on wearable devices. Although wearable devices, such as smartwatches, offer a convenient means to identify daily activities, they prove impractical when dealing with core aspects like sleep, eating, and work, where consistent device-wearing is unfeasible. Hence, the implementation of a system that circumvents the need for wearable devices, integrating Machine Learning to achieve high prediction accuracy, stands as an effective and forward-thinking solution.

Although there are numerous aspects of daily routine, this application primarily focuses on four main areas. By concentrating on sleeping patterns, tracking location, monitoring food nutrition, and tracking emotions, we aim to understand and predict these aspects of human behaviour and assess whether their patterns contribute to productivity. The following paragraphs explain those four components and their functionalities.

It begins with sleep monitoring and recognizing the critical impact of sleep on physical and mental health. By monitoring sleep patterns, users can identify areas for improvement to optimize sleep quality. Additionally, the application offers location prediction capabilities, potentially revolutionizing business and daily routines, by providing insights for targeted marketing, personalized services, and optimized operations. However, accuracy in location prediction is vital to ensure user satisfaction. The application also delves into emotion recognition, understanding the unpredictable nature of human emotions, and offering suggestions and a weekly emotion analysis report to help users maintain a positive daily routine. Lastly, it monitors users' food habits and nutrient intake through image processing

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technology, guiding healthy eating habits and food choices contributing to a more productive and health-conscious lifestyle. It is worth mentioning that all the monitorizations happen with users' permission. In summary, this multifaceted mobile application aims to improve various aspects of users' lives, from sleep quality to location-based services, emotional well-being, and food nutrition choices.

In the subsequent sections, we will explore related research, delve into the methodology details of our implementation, analyze the accuracy of the selected models in the results and discussion section, and finally, propose solutions to address the challenges identified in this introductory section.

II. LITERATURE REVIEW

Productivity is temporary and it is essential to be motivated to keep being productive. In the technological aspect, a considerable amount of research work has been conducted to develop wearable and non-wearable devices such as watches, belts, cameras, etc. to overwatch users' behaviors and notify the necessary changes to make users' lives more productive. This section discusses and compares those research works.

Several studies have explored the use of mobile sensors for sleep monitoring. Unsupervised learning has been a great choice in clustering the sleep stages of users. Research has used a k-means clustering algorithm to group accelerometer and gyroscope data into different sleep stages. Their approach achieved an overall accuracy of 75.4% in detecting sleep stages [1]. Similarly, another study has utilized a self-organizing map (SOM) algorithm to cluster physiological signals obtained from wearable devices to detect sleep stages. Their approach achieved an accuracy of 90.9% in detecting sleep stages [2]. To get a better view of the sleeping behavior, it should be measured statistically. The major problem with this approach is obtaining a labeled dataset of people's sleeping time. Hence many researchers tend to follow an unsupervised pattern.

One of the research projects has followed a supervised learning pattern and has used the accelerometer and gyroscope sensors to detect sleep and wake cycles and estimate sleep quality. They trained a support vector machine (SVM) classifier using features extracted from sensor data and achieved an accuracy of 86.6% in detecting sleep and wake cycles [3]. Not only the sensors in the phone can be used to detect sleeping behavior, but also its other features such as locked state and charging state can be used. For example, when a user is sleeping mobile phone is locked. This research also has missed the light sensor which can give drastically different values in the sleeping time compared to other times of the day. Users' properties such as age, gender, occupation, and marital status can also affect one's sleeping behavior. This research can be improved more using user's properties and mobile phone non-sensor data.

Location prediction using machine learning has been a popular research topic in recent years. Researchers have used various techniques and datasets to predict users' next location. One commonly used approach involves predicting the next locations of various users utilizing a single, comprehensive dataset. This shared dataset contained location histories, timestamps, and relevant features collected from a diverse group of users across a metropolitan area [4]. Shared datasets can result in a loss of individuality, making it challenging to accurately capture highly personalized patterns and preferences, thus leading to less accurate predictions for specific users. Additionally, shared datasets may struggle to accommodate highly personalized models and may not generalize well across all user groups.

Some of the studies have utilized only one machine learning algorithm to predict both the latitude and longitude of the next location [5]. Similarly, some of them have utilized only two machine learning algorithms (i.e., random forest and support vector machine) for the same purpose[6]. The limited use of machine learning algorithms can lead to suboptimal accuracy levels, as different algorithms have different strengths and weaknesses. It is important to utilize multiple machine learning algorithms in location prediction models because it leads to identifying the most accurate algorithm for a particular dataset and improves the accuracy of the prediction.

Recognizing emotions through mobile phone face detection using image processing has been the subject of extensive study. There have been many models and research done in this field, each with its own set of pros and cons. Some studies have reported high accuracy levels, while others have not been able to deliver good system features including accuracy. Existing related works on emotion recognition using image processing have only been able to classify the specific emotion of the relevant user. In the study "DeepEmotion: Facial Expression Recognition Using Deep Learning and MobileNet" by F. Sharmila, S. Priyanka, and S. Jeevitha, the authors suggest a deep learning-based method using the MobileNet architecture to recognize facial expressions on cellphones [7]. The system accomplishes real-time emotion recognition from facial photographs with great accuracy. "Mobile Facial Expression Recognition Using Local Binary Patterns and Support Vector Machines" by K. Patel and P. Patel focuses on identifying facial emotions on mobile devices using Local Binary Patterns (LBP) and Support Vector Machines (SVM) [7]. The suggested method successfully

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recognizes emotions in real-time and with high accuracy but for only a limited scope of emotions. In "Emotion Detection from Facial Expressions on Mobile Devices Using Transfer Learning" by R. G. Badamasi et al., the authors suggest an emotion identification system that makes use of transfer learning and convolutional neural networks for real-time emotion detection on mobile devices [8]. The study demonstrates that transfer learning increases recognition accuracy while reducing computational complexity.

While these works have made significant contributions to the field, they also highlight the gaps and limitations in existing algorithms for emotion recognition using image processing. Also, the noted fact is that most of the previous research only just recognizes the emotions without any further processes for improving the user's well-being. In our proposed system, we aim to provide high accuracy levels of emotions by increasing users' productive well-being.

Although food photos on smartphones can be automatically processed to estimate nutrition, the accuracy varies depending on the type of food. A solution to this issue is provided by an image-based nutrition assessment system that can recognize a variety of foods. One benefit of this system is that it can identify several images, but it needs a device that can support stereo mode [9].

A new model is introduced that estimates the size of each meal part for the whole input image by mapping the energy distribution of the food. Although this model can process images more quickly, it can only estimate one food portion at a time. The accuracy of food calorie estimation is increased using a unique framework for computerized food analysis utilizing photographs, although the procedure is still difficult.

The model is being trained using machine learning approaches to achieve high accuracy. The results display will be based on the classification. Moreover, there is an integrated system accessible for food image analysis [10]. For automated image-based food analysis, frameworks for end-to-end or multi-task processing (such portion estimation and recognition) are also available. There are research gaps and a narrow scope based on earlier studies and activities. In our system, we give special attention to dietary nutrition for people who value their health. This strategy is very helpful for people who want to eat a healthy, balanced diet.

Many previous research works have relied on external devices or wearables to monitor users' daily routines. However, in this study, we propose a system that utilizes mobile phone sensors and APIs to observe the user. With the assistance of ML strategies, the collected data is analyzed to obtain a better understanding of the daily routines. The analyzed data will be used to provide recommendations and a statistical view of the users' daily routines.

III. METHODOLOGY

The proposed system features a mobile application as its primary user interface, developed using the versatile cross-platform framework Flutter to ensure compatibility with both Apple and Android smartphones. This mobile app captures user interactions and presents outputs, while predictions and recommendations are generated on a remote server constructed with Python Django. Data storage is handled through the NoSQL database Firebase. The choice of a cross-platform framework for mobile app development aims to cater to a broad audience, while Python was selected as the backend language due to its rich resources in machine learning. The flexibility of a NoSQL database was favored to accommodate variable user data formats, and Firebase was chosen for its seamless integration with Flutter and its additional cloud services, including Authentication.

A high-level overview of the system is shown in figure 1. There are two points where the user interacts with the system. They are the mobile application and the web application. Data is collected from these ends based on user permissions. The collected data directly goes to the database or through the backend server. The backend server is used to do higher-level computations on data using ML models.

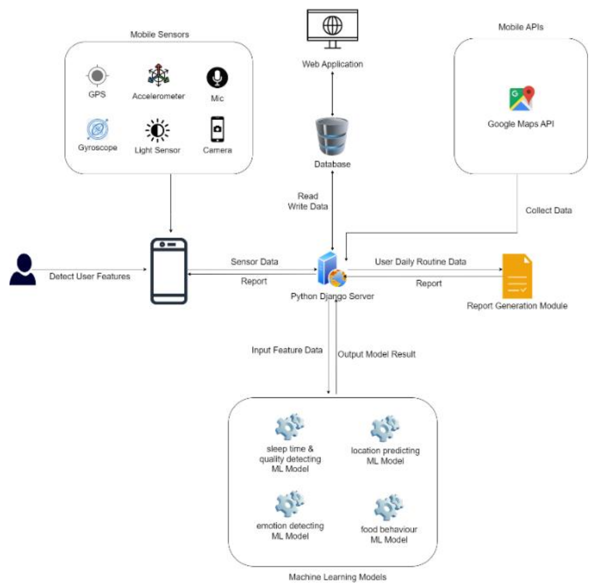

Figure 1: System Diagram

3.1 Understanding Users' Bad Sleeping Habits and Recommending Healthy Habits

In this research, understanding the user's sleeping behavior involves detecting the user's sleep time and wake-up time. To give recommendations, users' sleeping time and the

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light intensity level in the room while sleeping can be considered.

The user's age, occupation, marital status, and gender can be seen as properties of the user itself that affect one's sleeping pattern. When thinking about mobile phone sensors and the mobile phone itself, we can see that phone movements, locked time, charging status and light intensity can vary due to users' sleeping patterns. For example, when the user is sleeping the phone moves very rarely compared to when the user is awake. These data change drastically depending on the user's sleeping pattern. Weekday of the day is also a factor that affects the user's sleeping pattern. However, finding an algorithm to detect users' sleeping time manually is nearly impossible. ML is the technique we picked for this. Usually, ML is used to predict future values. But this is a use case where ML is used to find a complex algorithm.

We could not find an online data source for this ML model. Therefore, we decided to create one on our own. We developed a minimal mobile application that will ask users to enter their age, occupation, marital status, and gender when opening the app for the first time. Then the app shows a button that can be tapped when the user goes to sleep. Tap it again when the user wakes up. Whether the user is sleeping or not, the app will collect light intensity, movement data from the accelerometer, phone locked status, charging status, sleeping status, and date time every 5 minutes. Finally, we had a dataset that has the columns age, occupation, marital status, gender, light intensity, accelerometer x, y, z, phone locked status, charging status, day of the week, and user's sleeping status.

We needed two ML models to identify sleeping time and waking up time. We decided to calculate these two values in minutes. Initially, it was clear that users waking up and going to sleep times are discrete values. Therefore, we chose classification versions of Decision Tree and Random Forest and Logistic Regression algorithms to train the ML models. Finally, we will select the model with the highest accuracy. Since the output range is considerably large and the low amount of data, the accuracies of the models were too low.

Therefore, we reduced the number of different outputs by dividing a day into 144 equal parts where each part is 10 minutes long. We refer to a 10-minute part as a "slot" in the rest of the paper. With this approach, the model has to give a whole number between 0 and 143 inclusive of 0 and 143 as the output. For this, data for the whole day needs to be in one row. Each mobile phone's state data and sensor data are collected 143 times per day. Then all the columns count is 864.

We could see that, in the sleeping time dataset, almost every output falls between 125 and 143. In waking up dataset outputs fall between 30 – 57. In both datasets, only a small number of classes have training data. When trained this way, a classification model cannot predict classes outside the range in the dataset.

We finally came to regression versions of Random Forest Tree and Decision Tree and Linear Regression algorithms. They gave comparatively low errors. They are discussed in the "results and discussions" section.

The application will collect data for each slot and those will be used to calculate the sleeping time of the user. Usually, users sleep one day and wake up the next day. Therefore, the application needs to collect data for day x and day x + 1 to calculate the sleeping time of day x. When the user signs in for the first time, the user will be asked to wait for two days to access the sleeping pattern of the user. To provide recommendations, sleep durations of one week are considered and the user will be asked to wait 8 days to calculate the first set of recommendations. Recommendations are hard-coded texts that will be shown to the user based on sleep duration and light intensity in the bedroom.

3.2 Predicting User Location for Time Management and Personalized Services

Since user location patterns vary for each user, the specific data set is created for all users Instead of using generic shared datasets. The geolocator package was used to track individual users' locations with user permissions. With the user's explicit consent, their location data, including latitude, longitude, speed, and timestamp, was collected every 10 minutes via a background service. To maintain privacy, this data was stored locally in an SQLite database. Periodically, every 2 hours, the system checked for an active internet connection on the user's device. The locally stored data was securely transferred to Firebase if a connection was present. This two-step process of local storage and selective cloud transfer not only protected individuality but also facilitated seamless analysis. To ensure swift responses to users, a minimum tracking period of one month was established, focusing on consistent data rather than seasonal changes. Among the collected data, longitude, latitude, and timestamps were retrieved from Firebase and stored as separate columns in a CSV format. To prioritize user privacy and to obtain personalized location patterns, individual CSV files were created for each user. This approach ensured a high level of confidentiality for user information while enabling the development of precise and customized location prediction models.

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The datetime column in the dataset was utilized to create new features, namely weekday, hour, and minute, enhancing the dataset's richness. String categorical values like weekdays were encoded for effective processing. Empty rows were removed to ensure data quality. The dataset was then split into longitude (X) and latitude (Y) data frames. Subsequently, the output columns (longitude and latitude) were removed from each data frame, transforming them into features and targets. An 80-20 split was applied, separating the data into training and testing sets. To identify the best models, linear regression, decision tree, and random forest models were trained separately for longitude and latitude. To predict longitude and latitude coordinates, a streamlined function was developed. This function took the input date and converted it into relevant features. Predictions are made by loading the selected models for longitude and latitude.

In the mobile application, several essential plugins and APIs are utilized to display predicted locations and provide other location-based services. Predicted coordinates are processed using the Geocoding plugin, translating them into human-readable addresses for user understanding. The Geolocator plugin enables the app to track the user's real-time location using the device's Global Positioning System (GPS) or network, providing accurate latitude and longitude coordinates. The Google Maps Flutter plugin is employed to display Google Maps within the app, showcasing markers for both the user's current location and the predicted destination. Polylines are drawn on the map, visually connecting these locations. Additionally, the Google Maps Webservice package interacts with Google Maps APIs, specifically the Places API, enabling the app to search for nearby places based on predicted coordinates. Nearby places hosting special offers or events are visually highlighted on the map in different colors depending on the data coming from a separate web application we made for businesses looking to distribute their offers to clients.

3.3 Recognizing User's Emotions and Predicting the Daily Routine Analysis

This component allows users to grant camera access for real-time face detection processing. To identify and evaluate visual data accurately, convolutional neural networks are used in conjunction with deep learning because Convolutional Neural Network (CNN) is an enhanced architecture which capable of emotion detection very effectively.

To achieve high classification accuracy, a large dataset is required. For that, we have included five emotions in the dataset such as, happy, sad, furious, stressed, and neutral. While preprocessing facial images, it is essential to use image size, normalization of pixel values, and other necessary image processing methods. Then, train the images using the CNN model, and assess the learned model.

We developed a technique to detect people's emotions in their daily routines via a mobile application using a CNN-based image processing model. This section discusses the suggested system's technique for detecting, extracting, and classifying emotions from the images. The process can be divided into two steps such as collecting the image base dataset for the five emotion classes and image preprocessing of selected emotion images.

Here for the model training process, the emotion dataset has been taken from the Kaggle. To ensure that all images are of the same size, which is necessary for CNNs to efficiently process them, all images are preprocessed to the target pixel size of (48, 48) pixels. This process involves resizing input images to a consistent resolution, which significantly enhances the quality of input images and improves the accuracy of the output as well.

Overall, the preprocessing of images, feature extraction, and emotion classification are essential components of the system's architecture, making it a significant part of the mobile application. Also after detecting the specific emotion, it suggests user recommendations activities by retrieving the emotion history from the database. Once the user's emotion has been identified, the system will present their emotional history along with an analysis report based on their feelings. This report analysis will include bar charts and pie charts for weekly or monthly reporting. The main goal of this component is to provide busy individuals with an effective and fruitful analysis of their daily routines. Therefore, it is important to analyze people's emotional behavior after detecting their emotions because most individuals do not have a good understanding of their minds and how their emotions affect them daily.

3.4 Recognizing Foods and Nutrition

The purpose of this component is to develop a system that can recognize food nutrition and provide food reminders. The system uses a sequential algorithm to classify food images. The image dataset used in this system is obtained from Keras, and a hand-selected dataset from the internet is also added. This hand-selected dataset comprises 4,000 food images, which are combined with those sourced from Keras. To enhance the model's robustness, the data is preprocessed using data augmentation techniques to diversify the training set. The model architecture is based on convolutional neural networks (CNNs) and includes two convolution layers for feature extraction, two SoftMax layers for multi-class classification, and two pooling layers for dimensionality reduction. The neural network is trained on the prepared

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dataset to recognize foods from images and link them to their respective nutritional components. Moreover, the application has a mealtime reminder feature that allows users to set alarms and notifications to maintain their dietary schedules.

To achieve our goal of helping people maintain a healthy diet, we propose a system/application that can assist both healthy individuals and those with medical conditions. The system will measure the daily intake of food attributes and ingredients for users through their smartphone. By taking a photo of their meal, the user can determine the content of the food item with the help of our application. Our system will identify the food items in the photo using a Convolution Neural Network and estimate the food attributes by collecting data from the internet. This way, users can plan their daily calorie intake, regardless of whether they are obese or healthy.

IV. RESULTS AND DISCUSSION

This shows how the models used for the four main components are evaluated based on their accuracies.

For sleep monitoring, we needed 2 models to calculate the time the user went to bed and the time the user woke up. To find out the best algorithm 3 models for each calculation type were developed using Random Forest, Decision Tree, and Linear Regression. Overall, all these models have exceptionally good results. Table 1 shows Mean Squared Errors (MSE) of sleep time calculating models and Table 2 shows MSEs of waking up time calculating models.

Table 1: MSEs of Time Calculating Models

MSEs of sleep time calculating models	
Algorithm	**MSE**
Linear Regression	1.4570
Random Forest	1.2467
Decision Tree	0.6658

Table 2: MSEs of Waking Time Calculating Models

MSEs of waking time calculating models	
Algorithm	**MSE**
Linear Regression	1.0999
Random Forest	0.4678
Decision Tree	0.3194

With these results, Random Forest was selected as the best model to calculate the user's sleeping time. Such a low MSE raise concern about overfitting. A typical user sleeps between 125 and 143 slots and there are only 18 values between them. Our dataset contained 2 months of data collected from 20 different users. About 95% of data from the dataset fell under the above range. It is very unlikely a user sleeps out of this range. The same concept goes for the waking-up model too. Therefore, overfitting is an advantage in this ML model.

For location prediction, we tailored individual datasets for users by continuously tracking their movements. This personalized approach significantly improved prediction accuracy. We utilized three regression models Random Forest, Decision Tree, and Linear Regression for latitude and longitude prediction. As shown in Table 3, the Random Forest model stood out for latitude, achieving an impressively low MSE of approximately 1.94e-06, making it ideal for precise latitude forecasts. As shown in Table 4, for longitude, the Decision Tree model performed well with an MSE of about 8.38e-06, indicating good accuracy. We also acknowledged the balance between accuracy and privacy. While personalized datasets and specific models enhanced accuracy, users valuing privacy could opt for models like Linear Regression, offering acceptable accuracy with less data.

Table 3: MSEs of Waking Time Calculating Models

Algorithm	MSE
Linear Regression	2.43e-04
Random Forest	1.94e-06
Decision Tree	1.45e-05

Table 4: MSEs of Longitude Prediction Models

Algorithm	MSE
Linear Regression	1.79e-03
Random Forest	2.02e-05
Decision Tree	8.38e-06

For emotion recognition, the dataset was selected based on emotions such as happy, sad, angry, stressed, and neutral. After selection, the dataset was split into three parts: training dataset, validation dataset, and testing dataset. Figure 2 and figure 3 depict the training of images and the accuracy level with loss function achieved by the CNN algorithm model. The Keras model shown in figure 3 achieved an accuracy of 93.40% in

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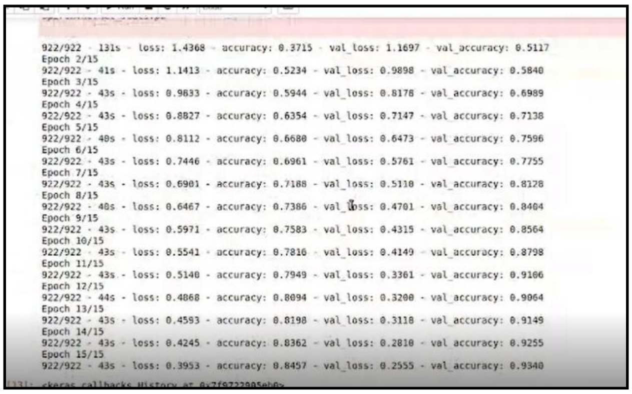
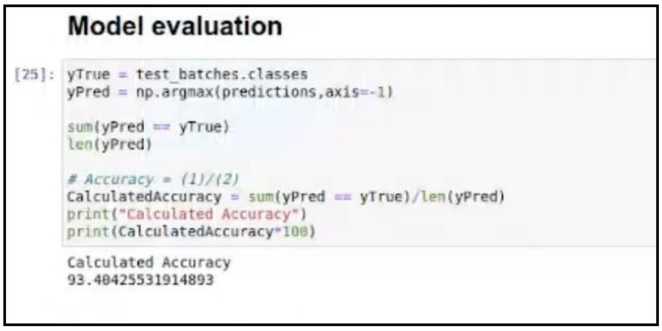
detecting emotions, making it a reliable model for emotion detection.



```
922/922 - 131s - loss: 1.4368 - accuracy: 0.3715 - val_loss: 1.1697 - val_accuracy: 0.5117
Epoch 2/15
922/922 - 41s - loss: 1.1413 - accuracy: 0.5234 - val_loss: 0.9898 - val_accuracy: 0.5840
Epoch 3/15
922/922 - 43s - loss: 0.9833 - accuracy: 0.5944 - val_loss: 0.8178 - val_accuracy: 0.6989
Epoch 4/15
922/922 - 43s - loss: 0.8827 - accuracy: 0.6354 - val_loss: 0.7147 - val_accuracy: 0.7138
Epoch 5/15
922/922 - 40s - loss: 0.8112 - accuracy: 0.6680 - val_loss: 0.6473 - val_accuracy: 0.7596
Epoch 6/15
922/922 - 43s - loss: 0.7446 - accuracy: 0.6961 - val_loss: 0.5761 - val_accuracy: 0.7755
Epoch 7/15
922/922 - 43s - loss: 0.6901 - accuracy: 0.7188 - val_loss: 0.5110 - val_accuracy: 0.8128
Epoch 8/15
922/922 - 40s - loss: 0.6467 - accuracy: 0.7386 - val_loss: 0.4701 - val_accuracy: 0.8404
Epoch 9/15
922/922 - 43s - loss: 0.5971 - accuracy: 0.7583 - val_loss: 0.4315 - val_accuracy: 0.8564
Epoch 10/15
922/922 - 43s - loss: 0.5541 - accuracy: 0.7816 - val_loss: 0.4149 - val_accuracy: 0.8798
Epoch 11/15
922/922 - 43s - loss: 0.5140 - accuracy: 0.7949 - val_loss: 0.3361 - val_accuracy: 0.9106
Epoch 12/15
922/922 - 44s - loss: 0.4868 - accuracy: 0.8094 - val_loss: 0.3200 - val_accuracy: 0.9064
Epoch 13/15
922/922 - 43s - loss: 0.4593 - accuracy: 0.8198 - val_loss: 0.3118 - val_accuracy: 0.9149
Epoch 14/15
922/922 - 43s - loss: 0.4245 - accuracy: 0.8362 - val_loss: 0.2810 - val_accuracy: 0.9255
Epoch 15/15
922/922 - 43s - loss: 0.3953 - accuracy: 0.8457 - val_loss: 0.2555 - val_accuracy: 0.9340
```

Figure 2: The Model Training Table and Loss Function



Model evaluation

```
[25]: yTrue = test_batches.classes
      yPred = np.argmax(predictions,axis=-1)

      sum(yPred == yTrue)
      len(yPred)

      # Accuracy = (1)/(2)
      CalculatedAccuracy = sum(yPred == yTrue)/len(yPred)
      print("Calculated Accuracy")
      print(CalculatedAccuracy*100)

      Calculated Accuracy
      93.40425531914893
```

Figure 3: Model Evaluation for Emotion Prediction

For food nutrition recognition, we created a custom model for food recognition and nutritional analysis, which had multiple layers to ensure good performance, but when we integrated it into the backend system, it misclassified a lot of food items. The accuracy dropped to an unacceptably low 50%, which meant we needed to improve it urgently. We realized that we needed a different approach, so we overhauled our algorithm to enhance accuracy. This led us to explore alternative algorithms that could better handle food classification. We also streamlined our dataset by selecting only the best images from the internet and enriched them through augmentation techniques to introduce more diversity into the training set. Our efforts paid off, and we saw a significant increase in accuracy. By using the new algorithm and reducing the data volume, our system's accuracy improved dramatically, which was in line with our goal of precise food recognition and nutritional analysis. This experience showed us that developing machine learning applications is an iterative and adaptable process, where strategic algorithmic choices and dataset management play pivotal roles in achieving accuracy and overall system efficacy.

V. CONCLUSION

In the realm of location prediction, the proposed research seeks to address persistent challenges by enhancing accuracy and user comfort through mobile APIs and feature engineering. It eliminates the need for wearables and integrates multiple machine-learning models for accurate latitude and longitude prediction. In the field of sleep monitoring, the research leverages smartphone sensors, phone states, and users' properties to develop an advanced non-wearable system that tracks sleep duration and quality, contributing to users' well-being. In emotion recognition, the project goes beyond conventional identification, aiming to predict daily routines based on detected emotions, offering personalized recommendations for optimized daily activities and increased productivity. Lastly, the research project focuses on recognizing food and nutrition. The research project takes a multi-faceted approach to address various gaps and challenges in location prediction, sleep monitoring, emotion recognition, and food nutrition recognition. The results section shows the accuracy of the ML models used to analyze the mentioned areas of the human daily routine. Leveraging mobile technology, sensor data, machine learning, and image processing, these innovative solutions aim to improve user experiences and overall well-being across different aspects of daily life.

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