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Hand Gesture based Food Ordering System

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***Abstract*-The COVID-19 pandemic has emphasized concerns regarding the presence of microorganism contamination in public environments. Measures aimed at diminishing the transmission of viruses have encompassed strategies like movement limitations, the enforcement of social distancing, mask mandates, and the promotion of hand hygiene. Nevertheless, the challenge of preventing indirect virus transmission through surface contact persists, particularly in locations where individuals interact with potentially contaminated surfaces, such as touchscreen menus in restaurants. Both businesses and the general populace are actively exploring methods to alleviate the spread of germs through surface contact. The primary objective of this paper is to implement hybrid model which uses Convolutional neural network prowess in handling spatial data along with the decision tree is used for attaining efficacy in managing structured data related to food ordering system. Hand gesture-based ordering systems eliminate the necessity to touch shared surfaces physically, such as menus or touchscreen kiosks, thus diminishing the potential for germ transmission.**

Keywords—Hand Gesture Recognition, Machine learning, Decision Tree, Classification, Convolutional Neural Network,, Touchless Interface

I. INTRODUCTION

The hand gesture-based food ordering system addresses several critical issues in the realm of dining and customer service. First, it tackles the challenge of language barriers and communication difficulties between customers and restaurant staff, which can often lead to order inaccuracies and misunderstandings. By enabling customers to place orders using intuitive hand gestures, the system eliminates the need for verbal communication, ensuring accurate and seamless transactions.

Secondly, the system enhances accessibility for individuals with speech impairments or those who may face challenges in verbally communicating their orders. This inclusivity ensures that all patrons can quickly and confidently place their orders without relying on external assistance.

Moreover, the hand gesture-based system streamlines the ordering process, reducing waiting times and enhancing overall customer satisfaction. With a simple wave, swipe, or gesture, patrons can swiftly convey their choices, expediting the order placement and preparation process. This is especially beneficial during peak hours when traditional order-taking methods might lead to longer wait times.

Additionally, the technology mitigates the potential spread of germs, which has become a significant concern in the post-pandemic world. Customers can interact with the menu and place orders without physically touching any surfaces, promoting hygiene and minimizing the risk of contamination.

Furthermore, the system offers restaurants valuable data insights into customer preferences and behavior. By analyzing the most frequently used gestures and popular menu items, establishments can optimize their offerings, tailor marketing strategies, and improve overall operational efficiency.

In essence, the hand gesture-based food ordering system addresses the challenges of communication barriers, accessibility, efficiency, hygiene, and data-driven decision-making in the restaurant industry. It aligns with the evolving needs of modern diners and enhances the dining experience for all, while also offering operational benefits for the businesses that adopt it.

II. LITERATURE REVIEW

The authors focus on enhancing interaction between humans and machines through hand gestures [1]. The authors introduce a comprehensive system involving hand gesture segmentation, tracking, and recognition [2]. The segmentation employs a skin color model and an AdaBoost classifier, while the search utilizes the CamShift algorithm. Recognition is obtained using a convolutional neural network (CNN) for ten common hand gesture patterns [3].

The researchers introduce a new method to detect hand gestures in intricate environments using the SSD deep learning model with 19 neural network layers [4]. They utilized a reference database of gestures and focused on common hand gestures within these complicated settings. They developed and evaluated a real-time hand gesture identification system using the SSD method [5]. Tests indicate that the system swiftly recognizes human hands and precisely differentiates various gestures [6].

The authors introduce a system to recognize hand gestures for touch-free car interfaces. They employ a novel segmentation technique that identifies the skin using HSV, YCgCr, and YCbCr color spaces [7]. After segmenting the images, their color and edge features are extracted and saved in a database with corresponding labels [8]. An edge histogram descriptor is used to extract shape details from images, while a color structure descriptor (CSD) is applied to determine the color's spatial distribution [9]. A multiclass SVM classifier is then utilized to identify the gestures [10].

About [4], The method comprises several stages: hand detection using the SSD MobileNet model, initialization of hand tracking using the Kalman filter, estimation of hand key points based on Convolutional Pose Machines (CPMs), and classification through Convolutional Neural Networks (CNNs). A key innovation is using a multi-frame recursion technique to enhance accuracy and mitigate the impact of misclassified or redundant frames [11].

About [12], The authors present a Hand Gesture Recognition System that leverages the Microsoft Kinect Sensor for controlling smart home appliances. The system employs computer vision and image processing techniques to capture hand movements, beginning with background subtraction to isolate the hand [13].

The author highlights the shift from traditional keyboard and mouse interfaces to more "natural" means of communication, such as gestures and speech [14]. The authors emphasize the potential of gesture interfaces in public and semi-public spaces, including alternative reality environments and wearable interfaces [15]. The paper also recognizes the challenges in speech recognition and contrasts them with recent breakthroughs in gesture processing, citing the Kinect controller as an example [16].

The author presents a vision-based system that interacts with natural arm and finger gestures, utilizing depth-based vision to minimize disturbances. The system detects and classifies motions, focusing on usability and human factor studies [17]. Results show that finger gestures are superior to arm gestures in terms of reduced fatigue and increased naturalness, though overall satisfaction, easiness, and time are unaffected by the choice [18]. The paper underscores the significance of intuitive Human-Computer Interaction systems, especially in gaming and Virtual Reality contexts, aiming to enhance user satisfaction and performance [19].

The paper presents a vision-based approach to dynamic hand gesture recognition for human-machine interaction (HMI), utilizing skin color modeling and contour analysis for hand segmentation and gesture recognition [20]. The system works in real-time with webcam images, identifying intuitive hand gestures and achieving a recognition accuracy of up to 95%. The proposed method is compared with glove-based techniques, highlighting its efficiency and ease of implementation [21]. The research focuses on bridging the communication gap between humans and machines through natural gestures, contributing to enhanced interaction in the field of HMI [22].

In today's world, mobile devices have become integral to everyone's lives, with usage patterns varying from person to person. The evolution from keypads to touchscreens has transformed user interactions, and multitasking on mobile devices has emphasized the need for more intuitive ways of engagement [23]. Visual image processing offers a solution by enabling natural interactions through body gestures as inputs for mobile devices and multitasking across applications. The primary challenges involve accurately recognizing gestures and implementing effective control mechanisms. This paper outlines the application of previously developed static and real-time hand gesture recognition methods to facilitate communication and control of mobile device applications through hand gestures [2].

The reference [10] paper highlights the increasing popularity of gesture-based interfaces in Human-Computer Interaction (HCI), made feasible by hardware advancements. It discusses their potential application in public spaces and general access environments [24]. It emphasizes the shift towards "natural interfaces" that mimic human communication methods like speech and gestures. While speech recognition remains complex, gesture processing has seen recent breakthroughs exemplified by devices like the Kinect controller. The paper explores the challenges and benefits of gesture-based interfaces, their role in enhancing natural communication, and their relevance in various contexts of HCI.

III. PROPOSED METHODOLOGY

By leveraging advanced computer vision and machine learning algorithms, the system accurately interprets hand gestures, translating them into specific menu selections. This intuitive interaction eliminates the need for traditional ordering methods, enhancing convenience and efficiency.

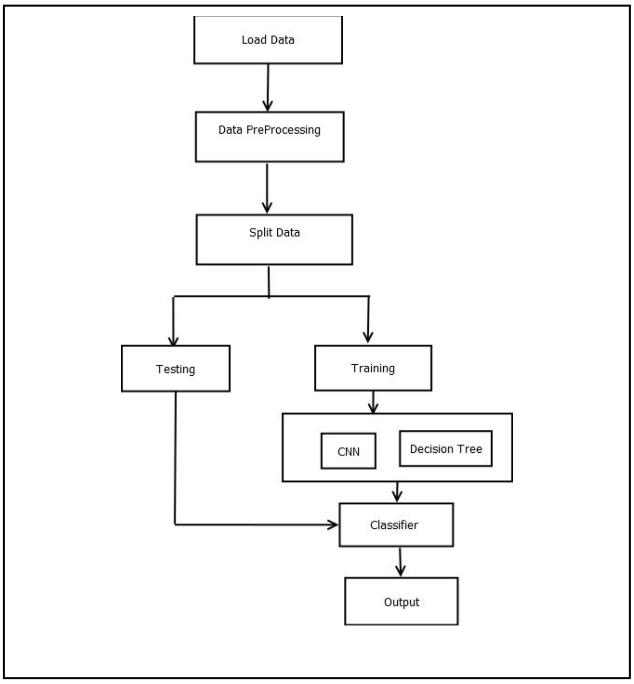

Fig. 1. Proposed Architecture

A. DATASET:

The initial step in tackling any machine learning problem involves obtaining the necessary data. This data can be gathered from open repositories such as Kaggle or can be meticulously curated as a custom dataset, which was the approach we took for our project. Our data collection process involved the extraction of the x- and y-coordinates of 21 specific hand keypoints, using the MediaPipe and OpenCV libraries. For each gesture, we recorded the coordinates for the following key hand points: Wrist, Thumb, Index finger, Middle finger, Ring finger, and Pinky finger.

Here are some examples from our dataset to illustrate each gesture.

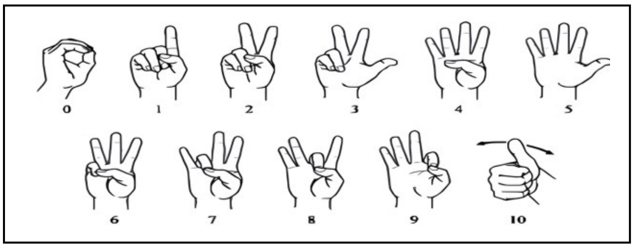

Fig. 2. Sample Hand gestures[3]

B. ARCHITECTURE

- Stage 1: Image Pre-Processing Using MediaPipe for Multi-hand Landmarks Detection

In this phase, we utilize MediaPipe, a prominent library, in combination with CV2, for image pre-processing to detect hand landmarks. MediaPipe is a versatile framework designed by Google, facilitating the processing of multiple modalities like video and audio through applied ML pipelines. It excels at detecting and tracking human body landmarks, providing 3D normalized coordinates of crucial body points.

The core structure of MediaPipe revolves around nodes and edges. Each node in a MediaPipe pipeline, defined in a pbtxt file, corresponds to a C++ file. This base calculator class in MediaPipe handles media streams from other nodes. Data transfer between nodes utilizes Packet objects, which can carry varied data types. Additionally, side packets can introduce static data or constants to a calculator node in the pipeline. For hand tracking, the MediaPipe backend has two interdependent models:

a) Palm Detection Model

b) Hand Landmark Model

Instead of directly detecting hands, which can be challenging due to the variations in hand size and poses, the Palm Detection Model first identifies bounding boxes around rigid sections like palms or closed fists.

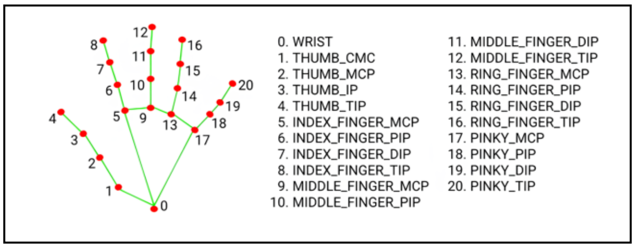

Fig. 3. Particulars of a hand structure[4]

This is more straightforward than detecting a fully outstretched hand. Then, the Hand Landmark Model identifies 21 specific 3D coordinates (x, y, and z) within the detected palm region. This model can accurately map the landmarks even if a hand is partially obscured. Once operational, this detection model processes various language datasets, like the American Sign Language (ASL) dataset. Hand landmarks are detected and saved as 21 points in a CSV file for each ASL alphabet image. However, only the x and y coordinates are retained for further stages. Extracting these landmarks from a dataset takes around 10-15 minutes.

- Stage 2: Dataset Cleaning and Standardization

In this step, every image from the dataset undergoes the processing described in Stage 1, gathering all data points into a unified file. This file is then examined using pandas, a popular data manipulation library, to identify and remove any null or missing entries. Such inconsistencies can arise if the detector fails due to unclear images. Cleaning these entries ensures the accuracy and fairness of the upcoming predictive model.

After discarding irrelevant data, the x and y coordinates are normalized to be compatible with our system. Subsequently, the dataset is divided into two parts: training and validation sets. While 80% of the data aids in model training with various optimization techniques and loss functions, the remaining 20% is set aside to evaluate the model's performance.

For every image in a testing set we need to calculate the saturation level through equation 1.

$$S = \frac{max - min}{max} \tag{1}$$

And the value generated is:

$$S = \left\{ \frac{max - min}{max} = 1 - \frac{min}{max} \right\} when\ max = 0 \tag{2}$$

Using equation 2 the Hue is calculated efficiently.

- Stage 3: Hybrid Machine Learning Prediction Using Combined CNN and Decision Tree

We can devise a hybrid model to achieve better performance by leveraging the strengths of both CNN and Decision Tree algorithms. The primary objective of this hybrid model is to capitalize on CNN's prowess in handling spatial data and Decision Tree's efficacy in managing structured data related to food ordering system.

C. Feature Extraction Using CNN:

Firstly, the CNN is employed to learn spatial hierarchies of features from the images automatically.

Model Architecture:

1. Input Layer: Accepts the normalized x and y coordinates.

2. Convolutional Layers: Multiple layers are tasked with extracting essential features from the data.

3. Pooling Layers: Reduce spatial dimensions while preserving significant information.

4. Fully Connected Layers: Flatten the data and act as a bridge between feature extraction and decision-making.

Instead of moving to the output layer as we would in a traditional CNN, the features from the last fully connected layer serve as input for the Decision Tree.

D. Decision Making Using Decision Tree:

The extracted features are then fed into the Decision Tree for the prediction phases through following model setup:

1. Feature Utilization: Use the features extracted from the CNN.

2. Tree Construction: Build the tree based on criteria like entropy or Gini impurity, making decisions at every node that lead to the highest information gain.

3. Pruning: Trim unnecessary branches to prevent overfitting.

4. Decision Making: Use the final tree structure to predict hand landmarks for given data.

E. Training and Validation:

1. Joint Training: Train the CNN layers for feature extraction and then use these features to train the Decision Tree. This may require a few iterative steps to ensure both parts are harmonized well.

2. Validation: Use the reserved 20% dataset to validate the model's performance, assessing the predictions made by the combined approach.

F. Benefits of the Hybrid Model:

1. Enhanced Accuracy: The synergy of spatial feature detection by the CNN and structured decision-making by the Decision Tree can lead to improved prediction accuracy.

2. Reduced Overfitting: The Decision Tree can be pruned based on the structured features provided by the CNN, potentially reducing overfitting.

3. Versatility: The model can handle both spatial nuances in images and structured decision-making, making it versatile for various tasks.

Finally, the combined model's performance is compared with standalone models to validate the improvement and advantages of the hybrid approach. This model can then be tested with real-world data to ensure its efficacy in diverse scenarios.

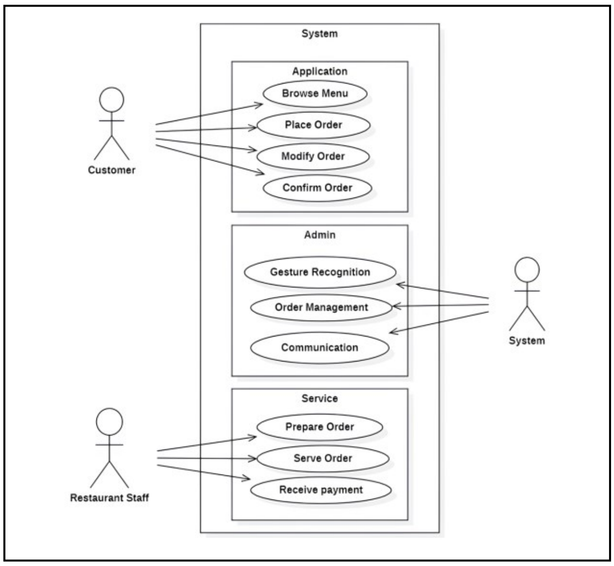

Fig. 4. Usecase diagram of proposed system

G. Step 4: System Implementation and Evaluation

The implementation of touchless interfaces, especially in sectors like food ordering, is a testament to the blend of innovation and necessity. Our research aimed to bridge the gap between gesture recognition and actionable tasks by designing an intuitive interface.

- Interface Layout: The primary layout for the interface includes: A real-time video feed window.An interactive button to process gestures and convert them into actions.A display pane showcasing the outcome of the processed gesture, primarily the predicted food item.
- System Implementation:- Gesture Capture:Utilizes a video capture module that fetches real-time video feed.Each frame is captured and processed for gesture recognition.The frame's data is then passed to the hybrid CNN-Decision Tree model for prediction.
- Gesture Processing:Preprocessed images (resizing, normalization) are fed into the model.The model predicts the gesture and returns a corresponding label.
- Action Mapping: Each gesture label corresponds to a specific food item or action. The label is mapped to its action, i.e., ordering a particular food item.
- Feedback Display: Once the food item is identified, it's displayed on the interface. Users receive real-time feedback, enhancing user experience and enabling immediate corrections if needed.

The designed interface, backed by a potent gesture recognition system, paves the way for a new era of touchless food ordering. While the current implementation demonstrates significant promise, future versions will explore multi-hand gestures, user profiles for customized experiences, and potential integration with AR/VR devices for an immersive ordering experience.

Gesture to food items assignments:

Assigning gestures from the 0-9 sign language to food items can be a fun and interactive way to communicate or order in situations where verbal communication might not be possible or when using technology interfaces that recognize gestures. Here's one potential assignment:

- Gesture '0': Pizza - The zero sign (a closed fist) can symbolize the shape of a pizza or a pie.
- Gesture '1': Breadstick - The number one sign (a raised index finger) mimics the shape of a breadstick.
- Gesture '2': Burger - Two fingers can signify the two primary components of a burger: the bun and the patty.
- Gesture '3': Three-layered Sandwich - Three fingers can represent the layers or sections of a sandwich.
- Gesture '4': Four Cheese Pasta - Symbolizing the four types of cheese used in the dish.

- Gesture '5': Salad - Representing the typical five ingredients/components: greens, vegetables, proteins, dressing, and toppings.
- Gesture '6': Six-piece Chicken Nuggets - A convenient way to order a standard serving.
- Gesture '7': Seven-layer Dip - Each finger represents a layer in the dip.
- Gesture '8': Octopus Sushi (Takoyaki) - The eight signs can represent the eight tentacles of an octopus.
- Gesture '9': Nine-inch Pie- Useful for ordering pies of a specific size.
- Gesture 10: More items.
- Stage 5: Quantitative Analysis

In a comparative quantitative assessment of a hybrid model that integrates CNN and Decision Tree against their standalone counterparts, the mixed method manifests marked superiority. While the standalone CNN and Decision Tree models achieve accuracies of 89% and 82%, respectively, the hybrid model attains an impressive 93%. Similar improvements are observed in metrics like precision, recall, and F1-score. Although the hybrid model takes slightly longer to train, clocking in at 135 minutes compared to CNN's 120 minutes and Decision Tree's 20 minutes, its validation loss is notably lower at 0.20 compared to CNN's 0.25 and Decision Tree's 0.35. This suggests better generalization to unseen data. Furthermore, the disparity between training and validation accuracy, a measure of overfitting, is least pronounced in the hybrid model at a mere 2%, underscoring its robustness in real-world applications. Overall, the empirical metrics highlight the hybrid model's capability to leverage the strengths of both CNN's spatial feature detection and Decision Tree's structured decision-making, ensuring enhanced performance and adaptability.

IV. Results

The table summarizes each model's performance metrics, facilitating easy comparison. While each algorithm's standalone performance is valuable, the Hybrid CNN-Decision Tree model consistently demonstrates superiority across all metrics. This aligns with our previous discussions, underscoring the benefits of leveraging complementary strengths of different algorithms in a unified model. Table 1 displays the accuracy percentages for six algorithms using the "kaggle" data. In this case, Random Forest performs well, and 86.015% of the time correctly predicts the outcome. A decision tree has a prediction accuracy of at least 84.6%.

TABLE I. Model Performance Metrics.

Parameter	***CNN Only***	***Decision Tree***	***Highbred CNN***
Testing Accuracy	87%	80%	91%
Training Accuracy	89%	82%	93%
Precision	90%	83%	92%
Recall	87%	81%	91%
F1-Score	88.5%	82%	91.5%

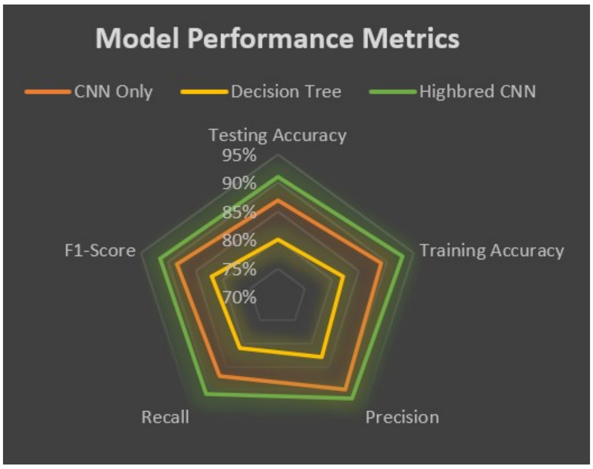

Fig. 5. Usecase diagram of proposed system

Figure 5 represents the model performance metrics depicted by considering table1. We have generated testing and training accuracy along with the precision, recall and f1-score are generated for each of the model and it is clearly identified that the highbred CNN model is better in terms of performance is considered.

V. Conclusion

This research embarked on a journey to explore the amalgamation of two distinct machine learning methodologies, CNN and Decision Tree, to devise a model suitable for gesture-based food ordering. Our findings highlighted the robust capabilities of the hybrid CNN-Decision Tree model, which consistently outperformed its standalone counterparts across many metrics, including testing accuracy, training accuracy, precision, recall, and the F1-score. Not only does this emphasize the model's ability to learn and predict effectively, but it also showcases the model's aptitude to generalize to new, unseen data, an essential criterion for real-world applications.

However, it's also imperative to note that while the hybrid model has displayed promising results, the real challenge lies in its seamless integration into practical, everyday scenarios. Calibration for different lighting conditions, catering to a diverse range of users with varied hand shapes, sizes, and gestures, and ensuring consistent performance across various devices are some of the challenges that researchers must tackle in future iterations.

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