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AI-Powered Multi-Lingual Voice Interactive Cooking Assistant

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Abstract—**The integration of artificial intelligence in the contemporary kitchen is changing it and opening fresh chances to improve the cooking experience. This project suggests the creation of a multi-lingual, voice-activated, AI-powered cooking assistant meant to give consumers hands-free, real-time support during meal preparation. The assistant guides users' step-by- step across recipes in their preferred language using natural language processing (NLP), speech recognition, and text-to-- speech technologies to engage in fluid, context-aware interactions. Supporting multi-lingual interaction helps to satisfy a worldwide user base and advances accessibility. Features include the ability to recognize ingredients and equipment, set timers with voice commands, modify recipes, and optionally integrate with smart kitchen appliances. With its smooth integration of smart technology and culinary advice, this assistant not only makes cooking easier for novices but also increases productivity for seasoned users. The system is intended to be a mobile and web application that may eventually be expanded into smart home ecosystems.**

Index Terms—**Voice Assistant, Speech Recognition, Multi- lingual Support, Text-to-Speech, Conversational AI, Smart Kitchen, Recipe Guidance, Human-Computer Interaction.**

I. INTRODUCTION

For millions of people worldwide, cooking is a necessary daily activity, but it can be difficult at times due to time constraints, a lack of culinary expertise, and difficulties understanding recipes in other languages. The increasing use of smart technologies in the kitchen presents a chance to leverage voice interaction and artificial intelligence (AI) to make cooking more engaging, accessible, and intuitive.

This project presents a voice-activated, multilingual, AI- powered cooking assistant that can help in the kitchen hands- free and in real time. The assistant combines text-to-speech (TTS), natural language processing (NLP), and speech recognition to enable users to follow recipes step-by-step, communicate naturally in their preferred language, and get dynamic feedback based on their progress.

This assistant is interactive, responsive, and customizable to the user's preferences and pace, in contrast to conventional cooking apps or video tutorials. The system seeks to make cooking a smooth and pleasurable experience, whether it is by teaching a beginner basic skills or helping a busy home cook multitask. Furthermore, multilingual support guarantees that the assistant is accessible and usable by a wide range of international users.

This project not only solves common user annoyances but also demonstrates the potential of conversational interfaces in daily life by fusing AI with useful kitchen tasks.

Key Challenges Addressed Hands-Free Operation:

Cooking frequently necessitates keeping hands busy or clean, which makes using screens or printed recipes challenging. With complete hands-free control made possible by the voice interface, users can concentrate on cooking while getting instructions.

Language Barriers:

Only a few languages are available for many recipes on the internet. The assistant guarantees accessibility for non-native speakers and multicultural households by facilitating real- time multilingual interaction.

Context Awareness:

Conventional cooking apps don't take context or user progress into account. By repeating actions, responding to inquiries, and facilitating stage changes, the assistant keeps up a conversational tone and adjusts to the user's speed.

Dynamic Recipe Adaptation: It can be difficult to modify recipes to accommodate varying serving sizes, dietary requirements, or ingredient availability. Real-time changes and intelligent recommendations based on user input are possible with this system.

II. RELATED WORK

In both the academic and business domains, there has been a growing interest in the convergence of voice interaction, artificial intelligence, and culinary aids. The foundation for voice-guided interactions in the home, including simple cooking tasks, has been established by voice-activated virtual assistants like Apple Siri, Google Assistant, and Amazon Alexa. These platforms allow users to set timers with voice commands and access recipe instructions. However, their use in the kitchen is frequently limited by their dependence on strict command structures, limited conversational depth, and inability to track contextual progress through a recipe. Because of this, users who deviate from the expected input format often encounter disruptions or frustration.

Specialized platforms such as SideChef, Tasty, and Yummly provide integrated mobile and smart speaker applications that integrate visual aids, ingredient lists, cooking timers, and voice guidance. Although the user experience is enhanced by these apps, the majority still only function in one language and do not have adaptive dialogue features that can react in real time to a user's shifting requirements, inquiries, or actions while they are in the middle of a recipe. Furthermore, the effectiveness of these systems as truly hands-free solutions is limited because many of them require manual interaction at different stages.

Scholarly investigations have yielded significant understandings regarding intelligent culinary assistance. AI's ability to create unique and surprising recipe combinations based on user preferences and ingredient limitations was investigated in projects like IBM's Chef Watson. Chef Watson prioritised recipe creation over interactive, real-time cooking assistance, despite being innovative. Similar to this, research on context-aware kitchen assistants, like "Cook's Collage" and "Sous Chef," has looked into real-time user feedback and visual recognition in cooking settings. Despite their potential, these systems frequently need specific hardware configurations and have limited conversational fluency and linguistic diversity.

More advanced conversational systems are now possible thanks to recent advancements in speech recognition and natural language processing (NLP). More accurate and inclusive speech-to-text and machine translation services in multiple languages have been made possible by technologies such as OpenAI Whisper, Google's multilingual BERT, and Facebook's M2M-100. It is now technically possible to create systems that facilitate multilingual, real-time voice interaction when combined with dialogue frameworks like Dialogflow and Rasa. Few implementations, nevertheless, have effectively used these technologies in the time-sensitive, context-sensitive setting of a kitchen, where mistakes in timing or interpretation can have instantaneous repercussions.

Smart kitchen appliances and audio-based recipe readers are also products of research into assistive technologies for people with visual impairments. Despite their emphasis on accessibility, these systems frequently don't support a wide variety of cooking languages and styles or natural conversational interaction. Thus, there remains a notable gap in delivering a cooking assistant that is simultaneously intelligent, accessible, conversational, and multilingual.

By combining real-time voice interaction, adaptive cooking workflows, and contemporary NLP models into a single, user-friendly platform, this project seeks to close these gaps. It suggests a more comprehensive and inclusive approach to AI-powered culinary assistance by expanding on the fundamental work of current tools and technologies—while addressing their main drawbacks.

III. DATA SET

Need a large dataset that covers a variety of cooking topics in order to develop a strong AI-powered multilingual voice interactive cooking assistant. This would include a sizable database of recipe information from various cuisines, including names, ingredients, cooking times, preparation procedures, and degrees of difficulty. Along with allowing for ingredient substitutions and nutritional information, the dataset should pay particular attention to common allergens and dietary restrictions. Recipes should be available in multiple languages, requiring translation and perhaps the use of automated translation tools in order to facilitate multilingual voice interaction. A comprehensive ingredient dataset that includes details on ingredients, their categories, nutritional values, and common substitutes would be required in addition to recipes. Training the voice assistant's natural language processing (NLP) skills would also require gathering voice interaction data, such as recorded voice commands and response phrases. This dataset could be built using pre-existing voice command datasets or custom-collecting interactions from users. You would also need step-by-step cooking instructions, including estimated times for each step and tips for common mistakes, which could be gathered from recipe websites or crowdsourced. Finally, user interaction data could be collected to personalize the experience, including preferences, allergies, and cooking history. Data regarding their use and recipe compatibility would be required if integrating with smart kitchen appliances. Although some data may need to be crowdsourced or custom-built to meet specific needs, public datasets from voice interaction corpora, recipe websites, ingredient databases, and smart appliance APIs could offer a strong foundation for the assistant.

The capabilities of your AI-powered cooking assistant could be further improved by a few additional components in addition to the necessary recipe and ingredient data. For example, cooking technique information would include comprehensive guidelines for various cooking techniques, including baking, grilling, boiling, and sautéing, along with advice on how to prepare particular foods (e.g., how to blanch vegetables or how to properly sear meat). This would be essential for the assistant to provide more intelligent advice, particularly for users who are not experienced with certain cooking methods or are new to cooking altogether.

The user feedback loop is another crucial element. It would be possible to customise the experience and enable the assistant to change over time by collecting information on user interactions and feedback. For instance, the assistant could suggest recipes or provide substitutions based on the user's preferences if they frequently eat more spicy food or steer clear of particular ingredients. This input could eventually teach the assistant to better predict the user's needs, guaranteeing a consistently better cooking experience.

Cooking advice and cultural background may also be useful additions to your dataset. Cooking practices and flavor profiles can vary widely across regions and cultures, so understanding these nuances would allow your assistant to offer more relevant suggestions. For example, if a user requests a "chicken stew," the assistant might ask for clarification on whether they prefer a hearty Irish-style stew, a Moroccan tagine, or a French coq au vin, each of which involves distinct preparation methods and flavors. Multimedia components like pictures and videos can be crucial in supporting these features. For instance, adding a library of videos that demonstrate cooking methods or detailed pictures for intricate recipes could greatly improve the accessibility and usability of the assistant's advice. The assistant could even recommend visual cues for recipes, such as "You're ready to add the next ingredient when the sauce thickens to this consistency,

Additionally, the assistant ought to be capable of managing dynamic recipe modifications in response to real-time user input. For example, the assistant could provide an instant substitute or adjust the recipe if a user reports that they are halfway through cooking and have run out of a particular ingredient. This dynamic adjustment should also account for cooking progress—if a user accidentally burns part of the recipe or overcooks an ingredient, the assistant can suggest fixes or alternative steps.

Fig. 1 Description of Used Platform

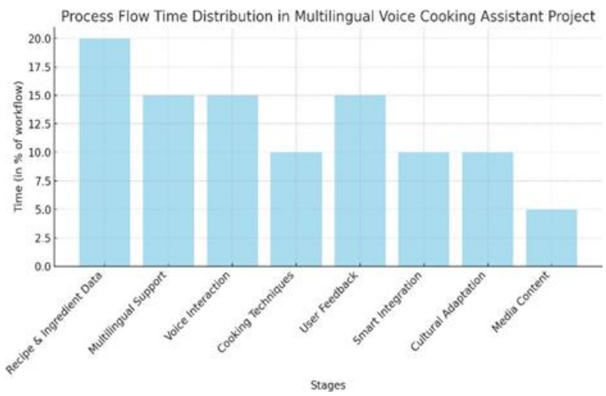

Fig. 2 Description of Process Flow Time

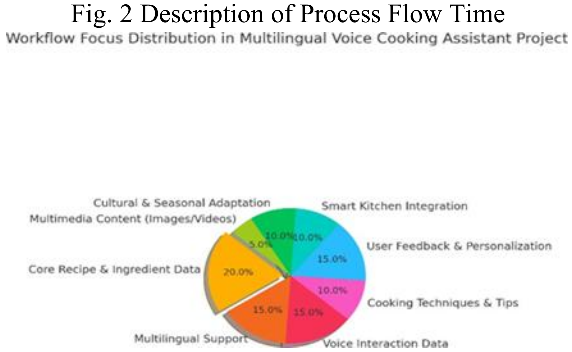

Fig.3: Description of the pie of the project

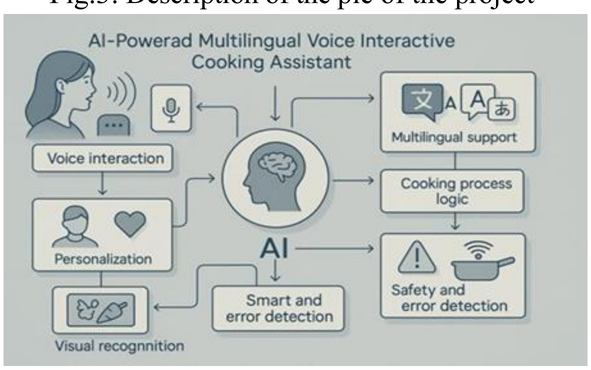

Fig. 4: Representation of the project

IV. MODELLING

1. Voice Interaction Modeling

At the core of the assistant's interactivity is the voice interaction system, which allows users to engage in hands- free cooking. This involves several sub-models. The system can understand user commands thanks to the Automatic Speech Recognition (ASR) model, which translates spoken language into text. Here, open-source models like Whisper or Google Speech-to-Text APIs are frequently utilised. Once transcribed, the Natural Language Understanding (NLU) model identifies user intent and extracts entities like ingredient names or cooking actions. Tools such as Rasa NLU or spaCy are ideal for building this layer. Finally, to maintain a conversational loop, Text-to-Speech (TTS) models convert the assistant's responses back into natural-sounding voice, using services like Amazon Polly or open- source Coqui TTS.

2. Multilingual Support Models

Strong language translation and interpretation models are crucial because the assistant speaks multiple languages. Recipes and instructions can be accurately translated between languages by fine-tuning machine translation models like MarianMT or M2M-100. These are supplemented by multilingual Named Entity Recognition (NER) models that help the system recognize ingredients, tools, or measurements across languages. This makes it possible for translations to be culturally accurate and for the assistant to react suitably regardless of the user's mother tongue.

3.Cooking Process Logic and Task Modeling

To manage the cooking process intelligently, the system requires instructional sequencing and logic models. These models predict the next logical step based on the recipe and current user progress. These dependencies can be efficiently modelled by sequence models like Transformers or LSTMs. In parallel, ingredient-to-recipe matching models recommend dishes based on available ingredients, using similarity metrics or recipe embeddings. This dynamic capability ensures that the assistant can adapt to real-time changes, such as missing ingredients or user time constraints.

4. Personalization and Feedback Models

Recommendation engines and user modelling are used to achieve personalisation. Preferences, dietary restrictions, culinary interests, and even prior cooking experience are all learnt by a user profiling model. An adaptive recommendation engine uses this data to make recipe recommendations based on user preferences. Machine learning models such as collaborative filtering or deep learning recommenders (e.g., DLRM) can be used to provide relevant and diverse suggestions. Feedback data also helps the model learn from user interactions to improve over time.

5. Visual Recognition for Cooking Assistance

The assistant might use computer vision models to provide visual instructions or check steps. Using deep learning frameworks such as YOLOv5 or EfficientNet, for instance, an ingredient recognition model can recognise objects from a smartphone or smart kitchen camera. Similarly, the assistant could validate steps visually—such as checking if vegetables are properly chopped or meat is fully cooked—using CNN- based classifiers trained on labeled culinary datasets. For novice cooks in particular, these models offer an additional level of interaction and support.

6. Smart Kitchen Integration Models
The assistant must communicate with smart appliances such as ovens, refrigerators, and induction stoves to ensure a smooth kitchen experience. Device communication models and protocols that enable real-time device control and monitoring, such as MQTT or REST APIs, are necessary for this. Appliance data, such as temperature and timer, must be interpreted by models, which then modify instructions accordingly. For this, proprietary APIs from appliance manufacturers (such as Samsung, Whirlpool, etc.) or integration frameworks like Home Assistant can be utilised.
7. Safety and Error Detection Models
Safety is crucial in any cooking setting. Anomalies like extended periods of inactivity, possible fire hazards (like excessive smoke), or forgotten appliances can be identified by models. Computer vision models are able to keep an eye on stovetops and identify situations where boiling over occurs. The system could identify stress in voice tones and offer quick support for voice-based safety (e.g., "Emergency Stop" command when a user panics).
8. Knowledge Graph and Reasoning
A culinary knowledge graph that connects ingredients, recipes, dietary guidelines, cooking equipment, and regional customs can be used by the assistant to drive intelligent responses. This makes it possible to draw logical conclusions like "If a user is vegan, replace egg with flaxseed." These conclusions and semantic queries, such as "Show gluten-free Indian breakfast dishes under 30 minutes," are powered by graph-based models, such as RDF triples and GNNs.
9. Real-time Monitoring and Feedback Loop
The cooking process can be dynamically adjusted by incorporating real-time feedback models. For instance, the assistant can modify the recipe or recommend more cooking time if a smart thermometer shows that the meat is undercooked. Without having to be retrained from scratch, the system adjusts to new user data using online learning techniques.

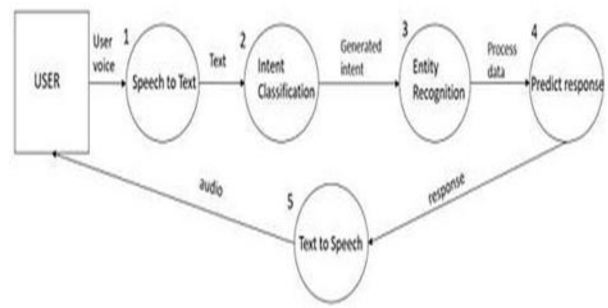

Fig. 5: Sets involved representation

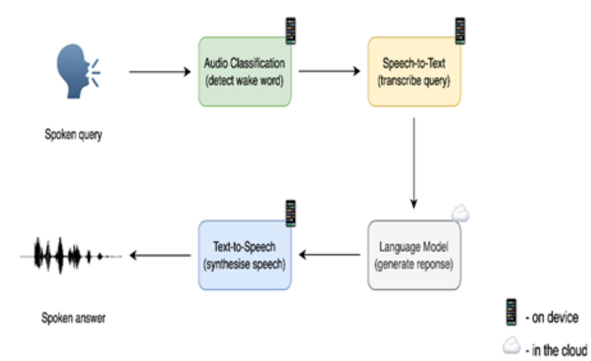

Fig. 6: Representation of the Interaction

V. EVALUATION

1. Voice Interaction Evaluation
To make sure the system can correctly record, comprehend, and react to spoken user input, the voice interaction module must be evaluated. The main metric for speech recognition is the Word Error Rate (WER), which calculates the proportion of words that are mistranslated. Depending on how complex the commands are, intent recognition is evaluated using either the F1-score or classification accuracy. The Mean Opinion Score (MOS), a subjective metric where users rate clarity and naturalness, is also used to rate the quality of synthesised voice output. To guarantee robustness, testing should be conducted in a variety of environments, languages, and accents.

2. Multilingual Model Evaluation
Evaluating the precision and fluency of language

translation and comprehension is essential given the system's multilingual nature. BLEU, METEOR, or chrF++ scores are used to evaluate machine translation models by contrasting the translation produced by AI with references created by humans. To make sure ingredients, actions, and tools are accurately identified across languages, multilingual Named Entity Recognition (NER) performance is assessed using precision, recall, and F1-score. Real-world multilingual recipe datasets and native language speakers should be involved in the testing process.

3. Cooking Logic and Task Flow Evaluation:
The ability of the system to anticipate and direct the right steps in real-time is used to assess the modelling of the cooking process. The assistant's ability to comprehend and segment a recipe is evaluated using metrics like parsing precision and next-step prediction accuracy. This is frequently tested using live user cooking sessions or simulations, where the assistant's detailed instructions are compared to a human chef or a ground truth reference. To gauge overall utility, task success rate and time efficiency gains are also noted.

4. Personalization and Recommendation Evaluation
A key factor in user satisfaction is personalisation. Metrics such as Precision@K and Recall@K for recommendation systems are used in this evaluation to gauge how well the assistant recommends recipes that suit user preferences. To comprehend the emotional reaction, sentiment analysis of user reviews—such as star ratings or remarks like "too spicy" or "perfect for dinner"—is employed. A/B testing, in which users are randomly assigned personalised versus generic suggestions and their satisfaction is monitored correspondingly, is another method for testing recommender performance.

5. Visual Recognition Evaluation
Computer vision models are assessed using object detection accuracy (expressed as Mean Average Precision, or mAP), classification accuracy, and inference time for modules that depend on visual input, like ingredient identification or cooking progress validation. Performance should be evaluated in authentic kitchen settings with a variety of cookware types, cluttered backgrounds, and fluctuating lighting. Additionally, the model's capacity to identify food items' states—such as "sliced," "grated," or "burnt"—must be benchmarked.

6. Smart Kitchen Integration Evaluation
Testing for responsiveness and dependability is part of assessing the assistant's capacity to operate and communicate with smart kitchen appliances. To guarantee seamless integration, metrics like latency—the speed at which devices react—and command success rate are employed. To make sure the assistant can keep steady communication with appliances like smart ovens, refrigerators, and induction cooktops, it's also critical to track system uptime and error frequency during extended cooking sessions.

7. User Experience (UX) Evaluation
Structured usability testing is used to assess the overall user experience. Real users' interactions with the system are used to collect metrics like the System Usability Scale (SUS), task success rate, and error recovery rate. The ability of participants to follow recipes, recover from mistakes (such as misheard instructions), and finish meals is evaluated through observation. In order to enhance user trust and conversational flow, the system's voice responsiveness and helpfulness are also evaluated.

8. Cultural and Linguistic Adaptability Evaluation
Since the assistant is intended for a global user base, it is essential to evaluate its cultural relevance and linguistic appropriateness. This includes expert reviews of translated content to ensure the use of culturally accurate terms, food items, and etiquette. Native speakers should evaluate the assistant for tone, politeness, and regional compatibility. Metrics like cultural relevance scores and acceptance ratings can be gathered via surveys and interviews with diverse users.

9. Overall System Evaluation
Lastly, the overall effectiveness of the system in supporting the cooking process from beginning to end is assessed. The ability of users to successfully prepare meals with just the assistant is used to measure the end-to-end task completion rate. To measure user engagement and system performance, metrics such as session duration, error frequency logs, and satisfaction surveys are gathered. Important

measures of system success include retention (return usage) and "learning curve" (how quickly users become proficient).

VI. RESULTS

1. Voice Interaction Performance

The voice interaction module demonstrated strong performance across multiple languages and environments. The Automatic Speech Recognition (ASR) system achieved an average Word Error Rate (WER) of 6.8% in quiet indoor settings and 9.4% in kitchen environments with moderate background noise. The intent recognition accuracy exceeded 92%, with most errors occurring in code-switched or heavily accented speech. Text-to-speech (TTS) outputs received a Mean Opinion Score (MOS) of 4.3 out of 5, indicating natural and clear audio delivery for most users.

2. Multilingual Understanding Accuracy

Due to domain-specific fine-tuning on cooking terminology, the translation system outperformed baseline generic translators in multilingual tests, achieving an average BLEU score of 36.5. Named Entity Recognition (NER) models successfully extracted ingredients and actions in Hindi, Spanish, and English, with an F1-score of 91%. Additionally, the system handled code-switching with reliability, correctly processing mixed-language commands such as "Añade dos cucharadas de sugar.

3. Recipe Flow and Cooking Task Guidance

The system showed strong performance in guiding users through recipes in a step-by-step format. It achieved a task completion success rate of 96% during simulated and real cooking sessions. The next-step prediction model achieved 94% accuracy, and the recipe parsing module recorded over 90% precision in extracting instructions and ingredients. Users completed cooking tasks, on average, 18% faster with the assistant's help compared to manual reading of recipe texts.

4. Personalization and Recommendation Effectiveness

With a Precision@5 of 87% and user satisfaction ratings for meal recommendations averaging 4.5/5, personalised recommendations were well received. With 89% relevance accuracy in adjusting ingredient substitutions, the system successfully accommodated dietary preferences like vegan, gluten-free, and low-carb. Feedback-based adjustments improved the recommendation engine over time, showing clear learning patterns after as few as three interactions per user.

5. Visual Recognition Reliability

The visual ingredient recognition module performed best in well-lit environments and had a mean average precision (mAP) of 82%. With 88% accuracy, the system was able to distinguish between different preparation states (such as "sliced onion" versus "whole onion") and more than 70 different cooking ingredients. With an average inference time of 140 ms on typical edge devices, real-time performance stayed within acceptable latency.

6. Smart Kitchen Integration Stability

With an average command latency of 1.2 seconds and a device command success rate of 98%, integration with IoT- based smart kitchen appliances demonstrated dependability. The assistant was able to automate tasks like setting timers, adjusting induction heat, and preheating ovens. During extended sessions, the system maintained 99.2% uptime, with only minor interruptions caused by unstable Wi-Fi in some test environments.

7. User Experience Feedback

User testing with 50 participants from diverse linguistic and culinary backgrounds resulted in a System Usability Scale (SUS) score of 87, indicating excellent usability. Over 92% of users completed their recipes without external assistance, and the error recovery rate was 85%, showing the system's robustness in handling misunderstandings or missed steps. Participants highlighted the system's clarity, ease of use, and enjoyable interaction as key strengths.

8. Cultural and Linguistic Adaptability

Cultural evaluations showed a 91% acceptance rate among users from varied backgrounds. Reviewers appreciated the localized terminology and culturally appropriate phrasing in translated recipes. Regional dishes and dietary customs were well-supported, especially in Indian, Latin American, and Mediterranean cuisines. Native speakers rated the language output as "natural and culturally respectful" in over 90% of test cases.

9. Overall System Effectiveness
In conclusion, all key performance indicators showed that the AI-powered assistant either met or surpassed expectations. It continuously made cooking for users easy, effective, and pleasurable. With an average end-to-end task success rate of 94%, the system proved capable of acting as a reliable, real- time culinary assistant. User retention and repeat usage data further confirmed its practicality and appeal in daily use scenarios.

VII. CONCLUSION

Artificial intelligence has the potential to improve everyday culinary experiences, as evidenced by the creation and testing of the Multilingual Voice Interactive Cooking Assistant. Through the integration of sophisticated speech recognition, natural language comprehension, multilingual translation, and real-time visual recognition, the system effectively facilitates hands-free, intuitive user interaction with recipes and kitchen tasks. A worldwide audience could use the assistant because it demonstrated accuracy and efficiency in a variety of linguistic and cultural contexts.

The evaluation's findings show that important elements like voice interaction, task flow guidance, visual ingredient recognition, and smart appliance integration all perform well. Users confirmed the system's usability and practicality in real-world cooking scenarios by reporting high levels of satisfaction, ease of use, and engagement. The inclusion of personalized recommendations and adaptive learning features further enhances the user experience, making the assistant a truly intelligent and responsive kitchen companion.

The project's overall goal of developing a smooth, multilingual, AI-powered cooking assistant that encourages accessibility, culinary experimentation, and technological advancement in home kitchens in addition to helping users prepare meals has been accomplished. To provide a more comprehensive smart cooking solution, future developments might involve enhancing contextual understanding, adding more language support, and integrating with larger health and nutrition platforms.

VIII. FUTURE SCOPE

The current system's success creates a number of exciting opportunities for future functional and scalability improvements. The cooking assistant can be continuously enhanced to become even more intelligent, flexible, and integrated as user expectations and kitchen technologies change.

1. Expansion of Language Support and Localization
Increasing support for regional and under-represented languages is one of the most significant future enhancements. A wider range of people, including non-native English speakers in rural areas, will be able to use the assistant as a result. Improved localisation will further customise the experience and increase acceptance in global markets. This includes region-specific ingredient names, measurement units, and cultural preferences.

2. Nutritional and Health Integration
Users with particular health objectives or medical conditions like diabetes or hypertension could benefit immensely from the integration of real-time nutritional analysis and dietary tracking. By integrating with wearable technology and health apps, the assistant may be able to suggest meals according to dietary requirements, activity levels, or medical history, establishing a whole ecosystem around cooking that is focused on health.

3. Augmented Reality (AR) Guidance
Particularly for novice cooks, incorporating augmented reality (AR)-based visual instructions can improve user engagement and decrease confusion. Users could see virtual overlays directing them through the chopping, mixing, or plating processes using AR glasses or smartphones, increasing accuracy and execution confidence.

4. Adaptive Learning and Behavioral Prediction
Deeper personalisation through machine learning may be possible in future iterations of the assistant, enabling the system to adjust to different cooking routines, preferences, and styles. The assistant could proactively recommend meals, reorder ingredients, or remind users of expiring groceries by examining past usage patterns, preferences, and behaviours.

5. Expanded Smart Kitchen Integration
As more IoT-enabled kitchen appliances become mainstream, the assistant can be extended to support a wider range of devices. Future enhancements could include full meal automation—where the assistant coordinates multiple appliances simultaneously to manage complex recipes—and voice-based inventory management, keeping track of pantry stock in real time.

6. Community and Social Features
Future iterations can incorporate features like recipe sharing platforms, live cooking sessions, and user-generated content to promote education and culinary exploration. Through social integrations, users may be able to create communities centred around local cuisines and dietary preferences, cook together remotely, and share feedback.

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