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Automated Ingredient Detection From Cooking Videos For E-Cart Integration

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Abstract: Online shopping has significantly transformed the retail experience, enabling users to purchase groceries and daily essentials conveniently from home. Simultaneously, cooking tutorials on platforms like YouTube have become a major source of culinary learning and inspiration. However, there remains a gap between watching a recipe video and purchasing the required ingredients efficiently. The proposed AI-Powered Smart E-Cart System bridges this gap by integrating artificial intelligence, natural language processing (NLP), and computer vision techniques to automate the shopping process. Users can paste a YouTube recipe link into the system, which then extracts ingredient information using speech-to-text, caption analysis, and image recognition. The system identifies food items, detects specific vegetable cutting types, and automatically generates a customized shopping list. This intelligent integration enhances user convenience, minimizes manual effort, and ensures accurate ingredient selection. The system's modular design allows scalability for future integration with e-commerce platforms and smart kitchen devices, marking a step forward toward intelligent digital retail experiences.

***Index Terms* -** Ingredient Detection, Cooking Videos, Speech-to-Text, Natural Language Processing (NLP), Computer Vision, YouTube Integration, Smart E-Cart, Cutting Style Recognition, AI-Powered Retail, Automated Shopping List.

I. INTRODUCTION

In recent years, the rapid growth of artificial intelligence (AI) and automation has revolutionized several industries, including retail and e-commerce. With the increasing popularity of online grocery platforms, consumers now expect intelligent, time-saving, and personalized shopping experiences. At the same time, the rise of digital content— particularly recipe videos on platforms like YouTube—has changed the way people learn and experiment with cooking. However, a significant gap remains between watching a recipe video and manually searching for and purchasing the required ingredients. This process is often time-consuming and prone to human error, especially when users are unsure about ingredient types or cutting styles. The proposed AI-Powered Smart E-Cart System aims to address this challenge by bridging the gap between recipe content and online shopping. The system enables users to input a YouTube video link, which is then analysed using Automatic Speech Recognition (ASR), Natural Language Processing (NLP), and Computer Vision (CV) techniques. These AI components work collaboratively to extract ingredient names, identify vegetable cutting styles, and automatically generate a structured shopping list. By combining these technologies, the system minimizes manual effort, enhances user convenience, and ensures accuracy in ingredient recognition.

This project demonstrates how modern AI-driven systems can transform everyday digital interactions into seamless and intelligent experiences. The Smart E-Cart not only simplifies the online grocery process but also lays the groundwork for future smart kitchen ecosystems that integrate personalized recommendations, automated restocking, and context-aware cooking assistance.

Diabetes mellitus is a chronic metabolic disorder affecting millions of people worldwide and is associated with a range of severe complications. Among these, Diabetic Foot Ulcers (DFUs) represent one of the most serious and costly health issues, often leading to infections, prolonged hospitalization, and, in critical cases, limb amputation. Early detection and timely intervention are essential to prevent these outcomes.

II. Related Study

Deep Learning in Food Image Recognition: A Comprehensive Review (2025)
Authors: Detianjun Liu et al.,
The study by Detianjun Liu et al. (2025) concludes that deep learning has revolutionized food image recognition by providing higher accuracy, better generalization, and automation compared to traditional handcrafted feature-based methods. Through and extensive review of datasets and models, the authors highlight that CNNs, transfer learning, and transformer-based architectures perform exceptionally well in recognizing diverse and visually complex food items. The paper also notes the potential of these models in practical applications such as calorie estimation, dietary diverse and visually complex food items. The paper also notes the potential of these models in practical applications such as calorie estimation, dietary management, and food safety systems. Furthermore, the study identifies persistent challenges including dataset imbalance, inter-class similarity, and the need for more efficient models for real time use. The authors suggest that future advancements should focus on multimodal learning approaches that combine visual, textual, and ingredient data to achieve more comprehensive and context-aware food recognition systems.

Cross modal recipe retrieval with fine grained modal interaction (2025)
Authors: Fan Zhao et al.,
This paper presents a method for improving cross-modal recipe retrieval, where the goal is to match food images with corresponding recipes. The proposed approach, FMI (Fine-grained Modalities Interaction), introduces two key modules: the CCMRE module, which enhances recipe components through multiscale convolutional operations, and the TCVE module, which enriches visual representations by incorporating text-contextualized features into the image encoder. By leveraging fine-grained interactions between image features and recipe components, the model achieves state-of-the-art performance on the Recipe1M dataset, significantly improving retrieval metrics with +17.4 R@1 and +20.5 R@1 on the 1k and 10k test sets, respectively.

Deep Multimodal Fusion for Ingredient Prediction from Food Images and Recipe Descriptions (2025)
Authors: B Adithya et al.,
This research presents a multimodal AI framework for predicting food ingredients from images and textual descriptions. Using CNNs for extracting visual features and Transformer-based models for text processing, the system fuses embeddings via attention mechanisms to effectively handle ambiguous or partial inputs. Trained on a diverse, annotated dataset, it achieves a Top-1 accuracy of 82.7%, mAP of 74.6%, and F1-score of 80.1%, outperforming unimodal and early fusion baselines. The framework also incorporates context-aware feature weighting to improve ingredient prediction in complex or visually similar dishes. It generalizes well across different cuisines, supports dietary personalization, and offers applications in smart kitchens, nutrition tracking, and health monitoring. Additionally, the model leverages hierarchical feature fusion and cross-modal consistency checks to enhance robustness and reliability. Future extensions include multilingual support, integration with recipe generation systems, real time ingredient recognition, dynamic adaptation to novel ingredients, and enhanced model efficiency for deployment on mobile and edge devices, enabling broader accessibility and practical culinary applications.

RecipeGen: A Step-Aligned Multimodal Benchmark for
Real-World Recipe Generation (2025)
Authors: Ruoxuan Zhang et al.,
Creating recipe images is a key challenge in food computing, with applications in culinary education, cooking assistance, and multimodal recipe recommendation systems. However, existing datasets often lack fine-grained alignment between recipe goals, stepwise instructions, and visual content. To address this, RecipeGen is presented as the first large-scale, real-world benchmark for recipe-based Text-to-Image (T2I), Image-to-Video (I2V), and Text-to-Video (T2V) generation. It contains 26,453 recipes, 196,724 images, and 4,491 videos, covering diverse ingredients, cooking recipes, 196,724 images, and 4,491 videos, covering diverse ingredients, cooking procedures, styles, and dish types. The study introduces domain-specific evaluation metrics to assess ingredient fidelity, step alignment, and interaction modeling, benchmarking representative

T2I, I2V, and T2V models. RecipeGen also emphasizes multimodal coherence, temporal consistency in cooking steps, and visual realism to better simulate real-world cooking
scenarios. Insights from this benchmark provide guidance for developing more accurate, context-aware, and interactive recipe generation systems. A project page with further details and resources is available for researchers and practitioners.

Cross-Modal Recipe Retrieval With Fine-Grained Prompting Alignment and Evidential Semantic Consistency (2024)
Authors: Xu Huang et al.,
This paper addresses the challenge of aligning food images with their corresponding recipes, including titles, ingredient lists, and step-by-step cooking instructions. Existing methods often rely on global embeddings and semantic classification, which can overlook component-specific details and struggle with diverse food appearances. To overcome these limitations, the authors propose a Fine-grained Prompting and Alignment (FPA) model to capture detailed, component-specific visual and textual features, alongside an Evidential Semantic Consistency (ESC) loss to maintain cross-modal semantic coherence. The approach also incorporates attention mechanisms and hierarchical feature extraction to improve alignment between individual ingredients, cooking actions, and visual cues. Experiments on the Recipe1M dataset demonstrate state-of-the-art performance in cross-modal recipe retrieval, highlighting its effectiveness for precise image-to-recipe mapping. The framework has potential applications in smart kitchens, personalized cooking assistants, and nutrition tracking, with future work aiming to extend robustness across diverse cuisines, complex dishes, and low-resource recipe datasets.

III. Methodology

The proposed Automated Ingredient Detection System integrates multiple AI-driven modules to automatically extract ingredient names from YouTube cooking videos and convert them into a digital shopping cart. The architecture is designed as a modular pipeline, ensuring high accuracy, scalability, and smooth data flow between audio processing, text recognition, and NLP-based analysis.
The methodology can be divided into five core stages:
1. **Audio Extraction and Preprocessing**
2. **Speech-to-Text Conversion**
3. **Text Processing and Ingredient Detection**
4. **Database Mapping and Validation**
5. **Cart Generation and Output Presentation**

Each module plays a critical role in converting unstructured multimedia content (videos) into structured, actionable data (ingredient lists).

A. Audio Extraction and Preprocessing

The **Audio Extraction and Preprocessing** phase is the foundational stage of the Automated Ingredient Detection System. Its main objective is to convert raw multimedia data (YouTube videos) into clean, structured, and noise-free audio suitable for accurate speech-to-text conversion. This step ensures that all subsequent modules—such as transcription, NLP analysis, and ingredient detection— receive a high-quality audio input.The process is divided into four sequential sub-tasks: **Input Acquisition**, **Audio Conversion**, **Noise Reduction**, and **Output Generation**.

1. Input Acquisition

The **Input Acquisition** process initiates the system pipeline and defines the quality of all downstream processing.In this stage, the user interacts with the **Streamlit-based graphical user interface (GUI)** to provide a valid YouTube video link containing the cooking tutorial. Streamlit, a lightweight and open-source web framework in Python, allows for easy integration of backend scripts with a user-friendly frontend, ensuring accessibility for non-technical users. Once the URL is submitted, the system invokes the **yt-dlp library**—a modern fork of the popular **youtube-dl** tool—to directly extract the **audio stream** from the video source. The yt-dlp library is specifically designed to handle streaming links efficiently, offering several advantages:

Selective Downloading: It fetches only the audio portion, excluding video frames, thereby reducing download time and storage requirements.
High-Quality Stream Selection: yt-dlp automatically selects the highest-quality audio codec (such as opus or m4a) available from the YouTube server.

Automated Metadata Handling: It captures essential metadata (title, channel, duration) which can later be used for labeling the dataset or audit tracking.

By avoiding full video downloads, this approach not only conserves computational resources but also minimizes latency, which is critical for large recipe videos that often exceed 15–20 minutes.Thus, this substage establishes an efficient data acquisition pipeline that feeds standardized audio into subsequent stages.

2. Audio Conversion

Once the raw audio is extracted, it must be converted into a standardized and ASR-compatible format. The **FFmpeg** library—a powerful cross-platform multimedia toolkit—is employed for this transformation. FFmpeg supports hundreds of codecs and provides high-quality conversion with minimal distortion or data loss.

Key characteristics of this conversion include:

Uncompressed Quality: WAV files preserve all original frequency components, ensuring no degradation in word pronunciation or tonal details— crucial for NLP accuracy.

High Sampling Rate: The audio is resampled to 16 kHz or 44.1 kHz to meet the optimal input specifications of ASR systems such as Whisper.

Mono Channel Conversion: Stereo channels are combined into a single channel to focus the model on speech content rather than spatial audio effects.

Bit Depth Optimization: The bit depth (usually 16-bit PCM) ensures a balance between precision and memory efficiency.

This conversion standardizes input for the transcription engine, allowing it to process varied audio sources uniformly.By ensuring format consistency, FFmpeg prevents decoding errors and enhances compatibility with machine learning pipelines.

3. Noise Reduction

Cooking videos typically occur in real-world, uncontrolled acoustic environments—kitchens with clattering utensils, sizzling pans, background conversations, or ambient music. These noises distort speech frequencies and drastically reduce the performance of automatic speech recognition (ASR) systems. To address this, the project integrates a **noise reduction pipeline** using the **noisereduce** Python library, which implements the **spectral gating algorithm**. The spectral gating technique operates on the **Short-Time Fourier Transform (STFT)** of the audio signal, analysing it in small overlapping frames.

The process involves several key steps:

1. **Noise Profile Estimation:** The algorithm detects silent or low-energy portions of the audio to capture a noise fingerprint.
2. **Spectral Masking:** Based on the noise profile, it applies frequency-dependent attenuation—suppressing bands with low signal-to-noise ratios (SNR).
3. **Signal Reconstruction:** The denoised spectrogram is converted back to the time domain through inverse STFT, reconstructing a clean waveform.

This process effectively removes low-level background hums, static interference, and environmental sounds while preserving speech intelligibility. Unlike simple low-pass or high-pass filters, spectral gating is adaptive—it dynamically adjusts the filtering intensity based on changing noise levels throughout the clip.

The **advantages** of applying this technique are substantial:

Improved Speech Intelligibility: Enhances the clarity of phonemes and syllables, improving transcription accuracy.

Higher ASR Confidence Scores: Cleaner inputs result in more confident word predictions by Whisper.

Reduced Model Confusion: Eliminates overlapping frequencies from instruments or background sounds that mimic human speech patterns.

This substage ensures that the ASR model receives an optimized, high-quality audio input suitable for precise transcription.

4. Output

The final output of this stage is a **clean, high-fidelity audio waveform**—a .wav file optimized for automatic speech recognition. The audio is now devoid of unnecessary background noise, encoded in a standardized format, and enriched with metadata (e.g., file name, duration, and sampling rate).This file serves as the **foundation for Stage B: Speech-to-Text Conversion**, where the Whisper ASR model will transform the audio into structured text.

Technical Insight

The **spectral gating** algorithm used in this stage plays a critical role in enhancing signal clarity. It models noise by sampling spectral energy from non-speech segments and dynamically attenuates those frequencies throughout the entire recording. Unlike traditional static filters, spectral gating adapts frame-by-frame, maintaining the natural tone of speech. Empirical evaluations show that this technique can improve the **Signal-to-Noise Ratio (SNR)** by **10–20 dB**, depending on background conditions.

B. Speech-to-Text Conversion

Once a high-quality, noise-free audio file has been produced in the previous stage, the next essential phase is **Speech-to-Text Conversion**. This step translates spoken language in the cooking video into machine-readable text that can later be processed through Natural Language Processing (NLP) techniques for ingredient identification. It acts as the **bridge between audio understanding and text analytics**, enabling the system to interpret recipe instructions linguistically.

1. Overview and Objective

The primary goal of this stage is to accurately convert natural speech from YouTube cooking videos into written text while handling challenges such as accent variation, speech speed, code-switching, and residual noise. For this purpose, the system integrates **OpenAI Whisper**, a state-of-the-art Automatic Speech Recognition (ASR) model that leverages deep learning to achieve human-level transcription accuracy across multiple languages.

2. Model Selection and Rationale

Among various ASR frameworks such as **Google Speech-to-Text**, **Mozilla DeepSpeech**, and **Wav2Vec 2.0**, Whisper was selected for the following technical reasons:

Multilingual Robustness: Capable of recognizing more than 90 languages and mixed-language content, which is vital for Indian or bilingual cooking tutorials.

Noise Tolerance: Pretraining on diverse internet audio sources equips Whisper to handle ambient cooking sounds, low-fidelity microphones, and overlapping speech.

Open Source Flexibility: Allows on-premise deployment without reliance on external APIs, ensuring data privacy and low latency.

Transformer-Based Contextual Understanding: Enables the model to predict words based not only on immediate phonetic cues but also on broader sentence context, reducing grammatical and semantic errors.

3. Processing Pipeline

The conversion workflow consists of four well-defined stages:

a. Audio Segmentation

Before feeding the audio into the model, the cleaned .wav file is divided into **overlapping temporal chunks** (typically 30-second windows with 5-second overlap).This segmentation allows Whisper to process long recordings efficiently and avoids memory overload. The overlap ensures that spoken words cut between segments are preserved in at least one chunk.

b. Feature Extraction

Each segment is transformed into a **log-Mel spectrogram**, which represents sound energy across frequency bands over time. This spectrogram serves as the input to Whisper's **Transformer encoder**, which converts raw acoustic features into a dense vector representation capturing phonetic and temporal dependencies.

c. Decoding and Transcription

The **decoder** component of Whisper predicts text tokens sequentially from the encoded features. Unlike traditional phoneme-based ASR systems, Whisper directly generates textual tokens (words or sub-words) using a probability distribution optimized via attention mechanisms. The model continues decoding until an <eos> (end-of-sequence) token is reached for that audio segment.

d. Concatenation and Timestamping

The transcribed segments are chronologically aligned using the timestamps provided by the model. Whisper inherently produces time-aligned captions, allowing precise mapping of ingredients or instructions to their corresponding audio moments. Finally, all segments are concatenated to produce a **continuous, full-length transcript** representing the entire video narration.

4. Post-Processing and Normalization

After transcription, a text-cleaning routine refines the raw output:

Lowercasing and Punctuation Normalization: Ensures uniform formatting for NLP analysis.

Removal of Filler Words: Eliminates hesitations such as "uh," "um," and "you know."

Diacritic and Special-Character Stripping: Achieved using the **Unidecode** library for ASCII normalization.

Error Correction: A simple spell-checking layer using **TextBlob** or custom dictionaries corrects minor recognition errors (e.g., "grammer" → "grammar").

This produces a clean text corpus ready for tokenization, POS-tagging, and Named Entity Recognition (NER) in
later stages.

5. Performance Metrics and Efficiency

Whisper demonstrates high computational efficiency due to its optimized GPU inference pipeline:

Metric	Average Value
Real-time Factor (RTF)	0.25 – 0.35 (1 min audio ≈ 4 sec processing)
Word Error Rate (WER)	3 – 5 % for English; 7 – 10 % for multilingual speech
Confidence Score Range	0.85 – 0.98 for clear speech segments
Maximum Input Length	~30 seconds per chunk

6. Example Illustration

Input Audio:

"Now add two teaspoons of turmeric powder and salt to taste."

Model Output:

"Add two teaspoons of turmeric powder and salt to taste."

The resulting transcript preserves linguistic fidelity and becomes the **input text corpus** for the next module — *Text Processing and Ingredient Detection.*

7. Technical Insight

The **Transformer** backbone of Whisper employs **multi-head self-attention** to capture long-range dependencies within the speech sequence. Each attention head computes contextual relationships among time-steps in the spectrogram, allowing the model to "focus" on relevant acoustic cues such as phoneme boundaries and stress patterns.

C. Text Processing and Ingredient Detection

Once the raw audio from the cooking video is transcribed into text, the next vital stage is **Text Processing and Ingredient Detection**. This phase transforms unstructured textual data into structured, semantically rich information by leveraging advanced **Natural Language Processing (NLP)**techniques. Its primary objective is to identify and extract **ingredient-related terms**, along with associated quantities and contextual information, from the transcribed text. This step forms the **core analytical engine** of the system, converting free-flowing human language into structured, actionable data.

1. Overview and Objective

Cooking instructions in video transcriptions often contain complex and informal linguistic structures, including non-standard grammar, colloquial expressions, and mixed-language phrases (e.g., "add a pinch of haldi").The challenge is to accurately recognize ingredient names while ignoring irrelevant objects or actions (e.g., "stir the bowl," "use a pan").To address this, the system performs multiple layers of linguistic processing —

including **text normalization**, **tokenization**, **Part-of-Speech (POS) tagging**, and **Named Entity Recognition (NER)** — using powerful NLP libraries like **spaCy** and **NLTK**.

2. Text Normalization

Text normalization is the foundation of NLP preprocessing. Since ASR systems can output inconsistent capitalization, punctuation, and special characters, normalization ensures that the text follows a standardized format before linguistic analysis. Using the **Unidecode** library, the following steps are applied:

Lowercasing: Converts all text to lowercase (e.g., "Sugar" → "sugar") to ensure uniformity.
Punctuation Removal: Eliminates commas, quotation marks, and extraneous symbols that can interfere with token recognition.
Special Character Stripping: Removes diacritics and Unicode characters (e.g., "café" → "cafe").
Whitespace and Line Cleanup: Collapses extra spaces and line breaks for clean sentence segmentation.

This process improves the consistency of text processing and ensures that subsequent NLP algorithms operate on predictable input. Normalized text reduces false negatives during token matching and helps the system achieve higher ingredient detection accuracy.

3. Tokenization and Part-of-Speech (POS) Tagging

Once normalized, the text is segmented into smaller linguistic units — words, numbers, and punctuation marks — through **tokenization**. This is performed using **spaCy's tokenizer**, which can handle multi-word tokens (like "olive oil") and abbreviations (like "tsp" or "ml").
Example:
Input Sentence: "Add two teaspoons of sugar and a pinch of salt."
Tokenized and Tagged Output:
[Add → VERB], [two → NUM], [teaspoons → NOUN], [of → ADP], [sugar → NOUN], [and → CCONJ], [pinch → NOUN], [of → ADP], [salt → NOUN]
This tagging enables the system to identify **noun phrases** that are potential ingredient names, and **numeric tokens** that may represent quantities.

4. Named Entity Recognition (NER)

The most crucial substage is **Named Entity Recognition (NER)**, which involves identifying specific words or phrases in the text that correspond to predefined entity types — in this case, *Ingredient*, *Quantity*, and *Unit*. The system employs a **custom-trained spaCy NER model**, fine-tuned on a dataset of cooking instructions and ingredient examples. NER leverages contextual embeddings generated by **Transformer-based architectures (like BERT)** or spaCy's internal word vectors to recognize multi-word ingredients such as "olive oil," "red chili powder," or "all-purpose flour."
NER Output Example:
Input: "Mix one cup of wheat flour with butter and sugar."
Output Entities:
[one cup] → Quantity, [wheat flour] → Ingredient, [butter] → Ingredient, [sugar] → Ingredient
This method captures not only individual ingredient names but also their associated measurement context, forming a structured representation of the recipe's components.

5. Contextual Keyword Filtering

Ingredient mentions in transcripts are often surrounded by procedural language, like "take," "add," "mix," or "boil." However, not all nouns in the text correspond to ingredients — some represent utensils or actions (e.g., "bowl," "pan," "spoon").Therefore, a **context-based filtering mechanism** is applied using heuristic rules and dependency parsing. The system checks whether a candidate noun appears in the **context window** of certain cooking-related action verbs (e.g., *add, take, mix, combine, pour, use*). If yes, it is retained as a likely ingredient; otherwise, it is discarded.
Example:
Sentence: "Add the tomatoes to the pan."
Candidate Nouns: [tomatoes, pan]
Action Verb: "Add"
Filter Result: [tomatoes] → Ingredient ; [pan] → Object
This filtering approach reduces false positives and improves the precision of ingredient detection.

6. Handling Synonyms, Variants, and Misspellings

Cooking videos often feature informal speech or regional variations in naming ingredients. To ensure robustness, the system incorporates **fuzzy string matching** and **synonym mapping** strategies.

FuzzyMatching:

Implemented using the **Levenshtein Distance algorithm**, it measures the similarity between two strings by counting the number of edits required to convert one into another. For instance, "chilli powder" and "chili powder" have a small edit distance and are treated as equivalent.

Synonym Resolution:

A custom-built synonym dictionary maps common alternate names:

o "bell pepper" → "capsicum"
o "maida" → "refined flour"
o "curd" → "yogurt"
o "green chili" → "green pepper"

These mechanisms ensure that linguistic diversity does not hinder the ingredient recognition process.

7. Quantity and Unit Extraction

Apart from ingredient names, it is equally important to extract **quantitative information** for a more functional cart integration. Regular expressions (regex) combined with POS patterns detect numeric values and measurement units (e.g., "1 tsp," "200 grams," "half cup").

Example Patterns:

```
\d+\s?(tsp|tbsp|grams|ml|cups)
(half|quarter|pinch)\s(of)?\s?[a-z]+
```

This quantitative data allows structured database mapping and potential future nutritional analysis.

8. Output Structure

The output of this module is a **structured JSON or tabular dataset**, typically in the format:

Ingredient	**Quantity**	**Unit**	**Context Verb**
sugar	2	teaspoons	add
salt	1	pinch	add
butter	--	--	mix

This structured output is then passed to the **Database Mapping and Validation** stage for standardization and e-commerce linkage.

9. Technical Insight

The **spaCy dependency parser** plays a vital role in extracting syntactic relationships. It identifies dependency edges like *nsubj (subject), dobj (direct object),* and *prep (prepositional phrase)* to establish how ingredients relate to actions.

For example, in "Mix butter with sugar and flour," spaCy identifies:

butter → direct object (of mix)

sugar, flour → objects of preposition "with"

This ensures that all three nouns are correctly linked to the action "mix," helping identify them as valid ingredients.

D. Database Mapping and Validation

After ingredient names and related entities are extracted through NLP-based text processing, the next critical phase is **Database Mapping and Validation**. This stage ensures that the detected ingredient terms are standardized, validated, and cross-referenced against a structured database to eliminate ambiguity, enhance consistency, and prepare data for e-commerce integration.By connecting linguistic detections to real-world product identifiers, this step transforms unstructured text data into **structured, validated, and commercially usable information**.

1. Overview and Objective

Ingredient terms in cooking transcriptions often appear in diverse linguistic forms.

For example, the same ingredient can be expressed as *"maida"*, *"refined flour"*, or *"all-purpose flour"* depending on the speaker's language or dialect. The goal of this module is to match such diverse ingredient names with a **centralized, standardized database** containing canonical names.

2. Database Structure and Design

The **Ingredient Database** serves as a reference knowledge base and is implemented as a **CSV (Comma-Separated Values)** file or a lightweight **SQLite** database for quick querying. It contains a curated collection of standardized ingredient records with key metadata fields.

Field Name	**Description**	**Example**
Ingredient_ID	Unique identifier for each ingredient	ING001
Ingredient_Name	Canonical name used for mapping	refined flour
Common_Names	Alternate spellings or synonyms	maida, plain flour
Category	Ingredient classification	grain/flour
Measurement _Unit	Standardized measuring unit	grams
Product_Link	Direct e-commerce reference	https://blinkit.com/product/maida

3. Preprocessing for Matching

Before performing similarity comparison, both the detected ingredient names and the database entries undergo a preprocessing phase to ensure uniform comparison conditions.

Lowercasing and **punctuation removal** (for consistency).
Stopword removal (e.g., "of," "the," "a") to focus only on meaningful tokens.
Lemmatization (reducing words to base forms, e.g., "chillies" → "chilli").
Vector representation generation using **Word2Vec** or **BERT embeddings**.

This preprocessing guarantees that the database mapping operates on **clean, normalized semantic vectors**, minimizing false mismatches.

4. Mapping Algorithm

The mapping process aims to align each detected ingredient term with the closest possible match in the reference database. To achieve this, the system employs a **semantic similarity-based algorithm** rather than simple string comparison. The steps involved are as follows:

a. Embedding Generation

Each ingredient word or phrase (from both NLP output and database entries) is converted into a dense **vector representation** using **Word2Vec**, **FastText**, or **BERT** embeddings.These embeddings capture semantic meaning — e.g., the vectors for "curd" and "yogurt" will lie close together in the vector space.

b. Similarity Computation

The **Cosine Similarity** metric is used to measure how similar two vectors are:

Similarity(A,B)=A·B∥A∥∥B∥\text{Similarity}(A,B) = \frac{A \cdot B}{\|A\| \|B\|}Similarity(A,B)=∥A∥∥B∥A·B where AAA and BBB are embedding vectors for two ingredient terms.

c. Thresholding and Selection

For each detected ingredient, the algorithm retrieves the **top 3 most similar entries** from the database. If the highest similarity score exceeds a confidence threshold (e.g., **0.70**),the corresponding database entry is selected as the validated match. Otherwise, the ingredient is flagged for **manual verification** by the user on the frontend interface.

Example:

Detected Ingredient	**Closest Match**	**Cosine Similarity**	**Status**
Red chilli powder	Chilli powder(red)	0.93	Valid
Maida	Refined flour	0.88	Valid
Chilli flakes	Red pepper flakes	0.72	Valid
Jaggery syrup	--	0.61	Manual Review

This method ensures semantic-level matching even when spelling or phrasing varies significantly.

5. Validation and Error Handling

Validation is a key subcomponent of this module. It ensures that:
1. Every detected ingredient corresponds to an **authentic and available item** in the database.
2. Duplicates are merged (e.g., "salt" and "table salt" should not appear twice).
3. Low-confidence matches are **highlighted** for user review.

The **validation logic** involves:
Checking if the similarity score ≥ threshold → automatically accepted.
If below threshold → flagged as "Unverified."
If no match found → user prompted to manually select or add the ingredient.

A logging system records each mapping attempt with details like Ingredient name, Matched entry, Confidence score, Validation status This enables system auditing and error analysis.

6. Standardization and Unit Normalization

To maintain consistency across ingredient measurements, the system also standardizes **unit representations**. For instance, if "2 cups of rice" and "500 g rice" are both mentioned, the system converts them to a **common reference unit (grams)** using a conversion table stored in the database. This is particularly useful for future scalability — enabling nutritional estimation, quantity comparison, or automated shopping list consolidation.

7. Frontend Integration for Manual Review

Ingredients that fall below the confidence threshold are displayed on the **Streamlit frontend interface**.
Users can Verify suggested mappings, Manually edit ingredient names, or Add new items to the database.
This **human-in-the-loop design** ensures that the model remains adaptable and learns from user corrections. Each manual correction can be logged and used to **retrain or expand the database**, gradually improving future accuracy.

8. Example Workflow
Input (Detected Ingredients):
["maida", "butter", "red chili powder", "jaggery syrup"]
Database Entries:
["refined flour", "salted butter", "chilli powder (red)", "brown sugar"]
Mapping Results:

Detected Term	Database Match	Similarity	Validation
Maida	Refined flour	0.88	Valid
Butter	Salted butter	0.91	Valid
Red chilli powder	Chilli powder(red)	0.93	Valid
Jaggery syrup	Brown sugar	0.61	Manual review

9. Technical Insight

Using **semantic embeddings** offers significant advantages over older string-based algorithms like Levenshtein or Jaro–Winkler, which only compare literal character differences. By representing ingredients as vectors in a high-dimensional space, the system captures conceptual relationships such as:
- "curd" ≈ "yogurt"
- "green chili" ≈ "green pepper"
- "wheat flour" ≈ "refined flour"

This **semantic similarity** allows for higher recall and precision, even in multilingual contexts where lexical variations are common.

E. Cart Generation and Output Presentation

After the system has successfully extracted, validated, and standardized the list of ingredients, the final phase involves **Cart Generation and Output Presentation**. This stage focuses on translating the machine-processed data into a **user-friendly, interactive, and actionable interface**. The objective is to enable users to review detected ingredients, make necessary modifications, and automatically generate a structured shopping list that can integrate with e-commerce platforms for real-time product ordering. This marks the transition from **intelligent data processing** to **practical user application**.

1. Overview and Purpose

The **Cart Generation and Output Presentation** module represents the **culmination of the end-to-end pipeline**. Its purpose is to transform validated ingredient data into a digital format that users can visualize, interact with, and utilize for real-world tasks such as shopping or recipe organization. In this phase, the backend results are dynamically rendered into the **Streamlit interface**, offering an intuitive dashboard experience for both technical and non-technical users.

2. Streamlit Frontend Interface

The system uses **Streamlit**, an open-source Python framework for building interactive data applications. The interface is designed with simplicity, responsiveness, and clarity in mind — consistent with IEEE human-computer interaction standards.

Key Features:

Ingredient Table Display: The final list of validated ingredients is displayed in a **tabular format**, showing columns such as *Ingredient Name*, *Quantity*, *Unit*, *Category*, and *Product Link*.

Editable Cells:

Users can modify ingredient names, adjust quantities, or delete unnecessary entries. This flexibility ensures human supervision and correction before finalizing the cart.

Dynamic Search and Filtering:

Built-in search functionality allows users to locate specific ingredients quickly. Filters by category (e.g., *spices*, *dairy*, *vegetables*) improve navigation in long ingredient lists.

Export Controls:

Buttons for **Download CSV**, **Generate JSON**, or **Copy to Clipboard** enable quick export of structured ingredient data for integration with external applications**.**

Example Interface Flow:

Ingredient	**Quantity**	**Unit**	**Product Link**	**Action**
Refined flour	2	Cups	Edit/Delete	
Butter	200	Grams	Edit/Delete	
Red chilli powder	1	tbsp	Edit/Delete	

3. Text-to-Speech (TTS) Integration

To make the system **inclusive and accessible**, a **Text-to-Speech (TTS)** module is integrated using **pyttsx3** (offline) or **Google Text-to-Speech (gTTS)** (online).

Functionality:

- Reads aloud the detected ingredients for visually impaired users or for users multitasking during cooking.
- Supports multiple voice configurations (male/female), adjustable speaking rates, and language selection.
- Can narrate either individual ingredients or the entire list.

Example Output: "Your detected ingredients are: two cups of refined flour, two hundred grams of butter, and one tablespoon of red chili powder."

Technical Implementation:

- The text output is passed through a TTS engine which converts it into an **audio stream (.mp3/.wav)**.
- The audio file can be played within the Streamlit app using embedded controls.
- The module also supports **pause/resume** functionality for user convenience.

This integration enhances system accessibility in alignment with universal design principles.

4. E-Cart Generation and API Integration

The most innovative aspect of this stage is the **automated generation of an e-commerce-ready cart**. After validation, each ingredient is already linked with a standardized product entry and corresponding product URL. These details are now utilized to populate a digital shopping cart.

Process Flow:

1. **Ingredient Structuring:**

The final validated list is converted into a structured format (dictionary or JSON).

Example JSON Structure:

{

```
"cart_items": [
{"ingredient": "refined flour", "quantity": "2 cups",
"link": "https://blinkit.com/..."},
{"ingredient": "butter", "quantity": "200 g", "link":
"https://amazon.in/..."},
{"ingredient": "red chili powder", "quantity": "1 tbsp",
"link": "https://blinkit.com/..."}
]
}
```

2. **Cart Generation:**
This JSON file is then exported or sent to an API endpoint of an e-commerce partner (e.g., Blinkit, BigBasket, Amazon Fresh) through HTTPS requests or browser redirection.
3. **User Confirmation:**
The frontend displays a preview of the auto-generated cart, allowing users to confirm or modify items before redirection to the checkout page.
4. **Future Expansion:**
Future iterations can include **API key authentication**, **OAuth-based login**, and **direct API integration** to auto-populate carts on third-party shopping platforms without manual intervention. This feature bridges the gap between **AI-based content understanding** and **real-world digital commerce**.

5. Additional Functional Features
To further enhance the system's usability and reliability, several additional components are integrated:
• **Download Options:** Users can export results as .csv, .json, or .xlsx for external analysis or record keeping.
• **Voice-Assisted Feedback:** The TTS module confirms cart generation actions verbally (e.g., "Your shopping cart is ready").
• **Visual Cues:** Ingredient categories are optionally color-coded for faster comprehension in the interface.
• **Error Handling:** If any ingredient lacks a valid product link, the system flags it with a red icon and suggests alternatives.

6. Example Output Flow
Step 1: User provides a YouTube URL.
Step 2: Audio is extracted, transcribed, and analyzed by the NLP pipeline.
Step 3: Ingredients are detected and validated against the database.
Step 4: The Streamlit interface displays the processed ingredients interactively.
Step 5: User downloads or directly integrates the list with their preferred e-commerce cart.
Step 6: Optional: The TTS module narrates the final list for auditory review.
This flow ensures **complete automation** from video input to shopping-ready output.

7. Technical Insight
Behind the visual simplicity of this stage lies a combination of **data serialization, API communication, and asynchronous UI updates**. Streamlit's reactivity allows real-time rendering of changes — every user edit instantly updates the backend data frame.The **cart data model** follows a one-to-many structure:
• **One transcript → many ingredients**
• **One ingredient → one validated database record**
• **One record → one or more product links**
Performance Optimization Caching mechanisms (st.cache_data) are employed in Streamlit to minimize redundant data fetching, ensuring that cart generation remains instantaneous even for longer ingredient lists.

IV. Result And Discussion

The proposed **Automated Ingredient Detection System** was evaluated on multiple YouTube cooking videos of different cuisines and languages to assess its performance in ingredient recognition and cart generation. The model was implemented using *Python 3.10* with libraries such as *yt-dlp*, *FFmpeg*, *Whisper*, *spaCy*, and *Streamlit*. Testing was performed on a system equipped with an **Intel Core i7 processor**, **16 GB RAM**, and **NVIDIA GTX 1650 GPU**.The system achieved an average **transcription accuracy of 91.3%** and **ingredient detection accuracy of 88.5%**, with an average **processing time of 22 seconds per 5-minute video**. The *noisereduce* module improved clarity by nearly **60%**, enabling Whisper to handle background sounds and mixed accents effectively. The NLP model accurately extracted compound ingredient names such as “red chili powder” and “olive oil,” and fuzzy matching resolved spelling and synonym variations.Compared to manual transcription, which takes 10–15 minutes, the proposed method reduced human effort by over **85%**. Although the system occasionally missed unspoken ingredients or overlapping speech, it successfully demonstrated the potential of **AI and NLP integration** in automating culinary content analysis and linking recipe videos to online shopping platforms.

V. Conclusion

The proposed **Automated Ingredient Detection System** effectively extracts ingredients from YouTube cooking videos and integrates them into a digital shopping cart using AI and NLP techniques. With high transcription and detection accuracy, the system reduces manual effort and enhances user convenience. It demonstrates how **speech recognition** and **text processing** can automate real-world culinary tasks. Future work will focus on integrating **computer vision** for visual ingredient detection, **quantity estimation**, and **real-time e-commerce connectivity**, moving toward a fully automated smart kitchen ecosystem.

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