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RESEARCH ARTICLE

EvoRecipes: A Generative Approach for Evolving Context-Aware Recipes

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ABSTRACT Generative AI e.g. Large Language Models (LLMs) can be used to generate new recipes. However, LLMs struggle with more complex aspects like recipe semantics and process comprehension. Furthermore, LLMs have limited ability to account for user preferences since they are based on statistical patterns. As a result, these recipes may be invalid. Evolutionary algorithms inspired by the process of natural selection are optimization algorithms that use stochastic operators to generate new solutions. These algorithms can generate large number of solutions from the set of possible solution space. Moreover, these algorithms have the capability to incorporate user preferences in fitness function to generate novel recipes that are more aligned with the fitness objective. In this paper, we propose the *EvoRecipes* framework to generate novel recipes. The *EvoRecipes* framework utilizes both Genetic Algorithm and generative AI in addition to *RecipeOn* ontology, and *RecipeKG* knowledge graph. Genetic Algorithm explore the large solution space of encoded recipe solutions and are capable of incorporating user preferences, while LLMs are used to generate recipe text from encoded recipe solutions. *EvoRecipes* uses a population of context-aware recipe solutions from the *RecipeKG* knowledge graph. *RecipeKG* encodes recipes in RDF format using classes and properties as defined in the *RecipeOn* ontology. Moreover, to evaluate the alignment of *EvoRecipe* generated recipes with multiple intended objectives, we propose a fitness function that incorporates novelty, simplicity, visual appeal, and feasibility. Additionally, to evaluate the quality of the *EvoRecipe* generated recipes while considering the subjective nature of recipes, we conducted a survey using multi-dimensional metrics (i.e. contextual, procedural, and novelty). Results show that *EvoRecipes* generated recipes are novel, valid and incorporate user preferences.

INDEX TERMS Knowledge graph, ontology, computational creativity, recipe evolution, recipe, food.

I. INTRODUCTION

Culinary recipe creation is both an art and a science. The artistic aspect of a recipe involves the texture, taste, aroma, and presentation that require imagination, technical skills, and creativity. Just like artists, chefs express their understanding of traditional recipes, cuisines, and unique cooking styles by combining and replacing ingredients, assessing flavors, balancing ingredient quantities, and presenting food in an appealing way. On the other hand, the scientific aspect requires knowledge of physics, biology, and chemistry. Scientific aspect also involves the chemical reactions of ingredients (e.g., Maillard reaction, responsible for the browning of food and the development of flavor), the impact of biological microorganisms on food (e.g., yeast in bread baking, bacteria in fermentation processes, and enzymes in the ripening of fruits and vegetables), and the impact of physical processes (e.g., roasting, steaming, and boiling) on the flavor and texture of food. Recipe creation is based on experience, imagination, as well as an understanding of scientific principles and processes, which proves that cooking is both an art and a science.

Creativity in culinary recipes has gained more importance in recent years due to the increasing interest of people in

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food culture and memorable dining experiences. Demand for specialized recipes from sick persons, diet-conscious people, and food enthusiasts also complements culinary creativity. Moreover, the rise of the social web has made it easier for chefs to share their newly generated recipes (based on their experiences, intuition, & imagination) and get recognition for their culinary creativity. However, human creativity in culinary recipes has a few limitations: *(i)* Error - Humans may produce errors while creating a new recipe or may misjudge the outcome of a recipe; *(ii)* Biasness - Chefs may have biasness for certain ingredients based on their availability in a certain region or certain recipes that are well received by the customers. Similarly, chefs may have preferences for certain cooking methods based on their skills limitations, or experiences. These factors play a significant role in limiting creativity; *(iii)* Speed - Human chefs need more time and effort to generate novel recipes than computational alternatives. On the other hand, computational creativity in culinary recipes overcome human errors, not affected by biases, and can generate recipes at a much faster pace than humans.

Food is considered a computational artifact [1] and researchers are exploring the potential of computational creativity to generate novel recipes [2], [3], [4]. Also, with the evolution of the semantic web, machine-understandable recipes have gained more attention in recent years. Several food ontologies (e.g. FoodOn[1] [5], RecipeOn[2]) and knowledge graphs (e.g. FlavorGraph[3] [6], FoodKG[4] [7], RecipeKG[5]) have been developed in the last decade that facilitates interoperability and increases machine-understandability for the food domain. Creativity in recipes involves multiple techniques that include combining an unusual group of ingredients, replacing ingredients, or attempting alternative cooking methodologies. These techniques are implemented using various models including statistical language models [4] and transformers [8].

The main objective of this article is to explore the computational creativity in culinary recipes using evolutionary algorithms. Therefore, we have proposed an evolutionary framework *EvoRecipes* that uses Genetic Algorithm (GA) [9], [10] to generate novel recipes (in RDF format) based on user preferences. Quantitative and Qualitative evaluation functions are designed to check the alignment (of recipes with user-preferences) and quality of novel recipes that have been generated using *EvoRecipes* framework. *EvoRecipes* generates novel recipes by exploring different components of a recipe (such as ingredients, actions, and procedures). An initial population of context-aware recipe solutions is initialized from *RecipeKG* knowledge graph. *RecipeKG* encodes human-generated recipes in RDF format and is based on 0.8 M recipes dataset. *EvoRecipes* is based on the structure of recipes proposed in *RecipeOn* ontology and interact with the machine-understandable recipes. Finally, to improve the human understand-ability of novel recipes, we have used OpenAI GPT API (Davinci model) to generate recipe text from RDF format for newly generated recipes. In this article, we have the following contributions:

- *EvoRecipes* framework to evolve culinary recipes.
- *EvoRecipes* encodes recipes in RDF format (using classes and properties as defined in the *RecipeOn* ontology).
- *EvoRecipes* uses GA to explore the large solution space of encoded recipe solutions and are capable of incorporating user preferences.
- *GA* is used to create novel recipes using following recipe evolutionary operators
  -- Mutation: Ingredient Replacement
  -- Mutation: Action Replacement
  -- Mutation: Action Interchange
  -- Crossover: Alternative Procedure
- Proposed multi objective fitness function to evaluate the quality of novel recipes.
- Proposed qualitative metrics to evaluate the subjective parameters of novel recipes.
- Recipe RDF to Recipe Text Generation using OpenAI GPT.

The paper is organized as follows. In section II, related work is discussed. We have briefly explained the *RecipeOn* ontology and *RecipeKG* knowledge graph in section III, *EvoRecipes* framework and its components have been discussed in detail in section IV. In section V, we have discussed qualitative evaluation metrics. Experimental setup, experiment detail and comparison with related techniques is discussed in section VI. Finally, we present the summary and future directions in section VII, and section VIII respectively.

II. RELATED WORK

Exploring new and unique recipes is always in demand by food enthusiasts, health-conscious individuals, patients, and chefs. Novelty in recipes is being pursued with the help of computer-aided and artificial intelligence-based techniques. Computational creativity, a sub-field of artificial intelligence, has also been explored in the culinary domain. Various aspects of culinary science such as computational gastronomy [11], flavor gastronomy [12], flavor pairing [13], food perception [14], flavor perception [15], food pairing [16], [17], knowledge networks for robotic cooking [18], and sustainable food systems [19] have been investigated using computational creativity. The perception of food and flavor is influenced by several factors including the chemical relationships among ingredients, color, shape, temperature, and texture. In the culinary domain, computational creativity involves pairing and mixing ingredients in novel ways [20], [21], [22], [23], [24], [25]. Identifying associations among ingredients in different recipes, analyzing the co-occurrence of flavor compounds and colors [26], identifying frequent patterns among cuisines [27], utilizing cognitive

[1] https://foodon.org/
[2] https://hajirajabeen.github.io/EvoRecipesOntology/
[3] https://github.com/lamypark/FlavorGraph
[4] https://foodkg.github.io/
[5] https://hajirajabeen.github.io/RecipeKG

informatics [28], generating cooking actions from recipes [29], suggesting cross-cultural food preferences [30], and diet recommendation system [31] have recently been explored in culinary domain.

The internet is abundant with information, making it challenging to integrate all pertinent information with provenance for optimal food choice recommendation. Traditionally, food pairing choice of food experts depend on their experiences. However, Artificial Intelligence (AI)-based recommender systems have recently emerged as an alternative for providing food pairing recommendations. FlavorGraph [6] is one such system, a large-scale food-chemical graph that utilizes AI to predict relationships between food and chemical compounds. It's nodes contain information on either ingredients or chemical compounds, while the edges represent relationships among ingredients and chemical compounds. Another food recommendation knowledge graph FoodKG [7] provides personalized food recommendations based on user preferences (such as ease of preparation, convenience, spiciness, crispiness, and other generic requirements). However, FoodKG did not recommend and explore relationships related to actions and procedures involved in recipe.

A recommendation system [8] for ingredient and recipe selection has been developed that utilizes cooking tags and ingredients as inputs to suggest related options. However, due to limitations in the system's training on cooking-related knowledge, it sometimes recommends inconsistent recipe choices given a particular set of ingredients. In another effort toward recipe evolution (i.e. SmartChef [32]), a genetic programming approach has been employed to evolve the recipes encoded in a tree structure. Authors have tested their approach on a 128 recipe dataset. They didn't consider the semantics of recipe while generating new recipes. Moreover they have designed semi-automated fitness function. EvoChef [33] is an evolutionary approach to recipe generation that relies on recombining ingredients and instructions to generate new recipes, but this system has initial population of 08 recipes dataset consisting solely of potatoes. Additionally, it lacks critical information such as nutritional information, flavor, and ingredient pairing details. They validated recipes just through human feedback. In another effort Jabeen et al. proposed AutoChef that recommends recipes using genetic programming [3]. They have used the dataset of 75 recipes. However, AutoChef has limited ingredient and action replacement options. Moreover AutoChef did not focus on sequence of actions while performing the mutation on action node.

Antô et al. proposed an automatic recipe generation using genetic programming along with a language model is used for decomposition of recipe and then recomposing them to generate new recipes [4]. Authors worked on a limited set of recipes and while recombination of recipes they have used a limited list of ingredients and preparatory actions. They didn't ensure the proper classification of ingredient, actions and instructions for generating new recipes. A different recipe recommendation system based on user questions was proposed by Khilji et al. [34]. They have developed a question classification model through which user question is assigned a label. This class label is used by the recommendation engine for recipe recommendation. They have trained the model on a limited recipe dataset and the system is unable to classify the user questions to more specific categories. Therefore recipe recommendation is more general rather then specific to user questions. Novelty in recipes is also generated by updating actions, ingredients, and sequence of actions. On the similar concept recommending alternative ingredients for thai cuisine with suitable ingredients was proposed by [35] to generate new recipes. Another alternative ingredient replacement was proposed by Pan et al. [36]. They replaced ingredients based on resemblance estimation. All of these techniques used computational creativity to generate new recipes, including food pairing, flavor pairing, computational gastronomy, and ingredient substitutions.

Existing approaches uses small-sized recipe datasets with limited number of attributes. These dataset comprises of recipes represented in a similar or limited formats extracted from few recipe websites that restricts the model capability to improve machine-understandability of a recipe. These approaches attempted ingredient-substitution based on limited ingredient set and similarly substituted actions based on limited number of actions to generate new recipes. Also, these approaches lack in expressing sequence of actions, relationship between ingredients, and relationship between ingredients and actions. This can have significant impact on taste, aroma, and visual presentation of food item. Moreover, existing techniques focused on improvement of machine-readability while compromising the machine-understandability of data. Furthermore, many existing approaches also lack in quantifying the semantic validity of novel recipes. Finally, the machine generated novel recipes are difficult to understand by humans as these are in machine-readable format. In this article, we have covered all of these research gaps and generated novel recipes using *EvoRecipes* that are semantically valid, and available in human readable format. Moreover *EvoRecipes* generated recipes are machine-understandable and is based on *RecipeOn* ontology that has rich recipe knowledge and provides schema for ingredient-action and action-action relationships.

III. PRELIMINARIES

A. RecipeOn

RecipeOn[2] is a recipe ontology that not only helps to increase machine-understandability but also encodes important information pertaining to the recipe. It includes ingredients, actions, nutrition, and sequencing of instructions. *RecipeOn* ontology guides the user in preparing recipes as a systematic process. It facilitates not only providing information related to ingredients and actions but also the sequence of actions and ingredients related to each procedure. *RecipeOn* is helpful in

[6]https://www.allrecipes.com/recipe/8453018/easy-air-fryer-whole-chicken/

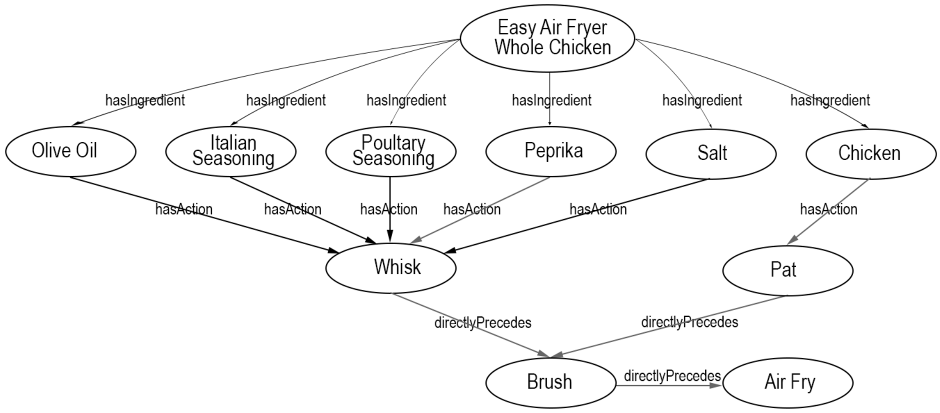


FIGURE 1. "Easy air fryer whole chicken"[6] recipe represented as a process based on classes and relationship of RecipeOn ontology.

evolving new recipes and personalizing the existing recipes for different of user preferences using alternative ingredients and alternative action relationships. Furthermore *RecipeOn* has the capability to map recipes as a process.

B. RecipeKG

A Recipe Knowledge Graph *RecipeKG* [7] is built using 0.8M-Recipes[8] that comprises 0.8 million human-generated recipes and collected from top-ranked recipe websites. It contains basic recipe details, a list of ingredients, nutritional information, and instruction statements. *RecipeKG* uses the concepts and relationships as specified in *RecipeOn* ontology. It represents the recipe as a process and defines the ingredient-action, action-action, and ingredient-action relationships. *RecipeKG* is based on a huge collection of 52.96 million instances and 209 million facts.

IV. EvoRecipes: A GENERATIVE APPROACH FOR EVOLVING CONTEXT-AWARE RECIPES

EvoRecipes is a recipe evolution framework that generates customized recipes based on user preferences. It has been built making use of *RecipeOn* ontology that represents the recipe as a process as shown in figure 1. Ingredients are categorized into three ingredient types (i.e. *MainIngredient*, *SideIngredient*, and *FlavorIngredient*) using three different object properties (i.e. *hasMainIngredient*, *hasSideIngredient*, and *hasFlavoringIngredient*). Each ingredient has an object property *hasAction* that determines the action performed on each ingredient. Actions have some sequence among themselves that is ensured by *RecipeOn*'s object properties (i.e. *seq* : *directlyFollows* and *seq* : *directlyPrecedes*).

In this article, we have proposed *EvoRecipes* framework (figure 2) that uses both evolutionary algorithm and generative AI to create custom context-aware and human-readable recipes. Evolutionary algorithms are based on the phenomena of survival of the fittest and calculate the fitness of an individual using a fitness function. Therefore, fitness functions are tuned to accommodate user choices and preferences. Moreover, recipes have been encoded using *RecipeOn* ontology which makes them not only machine-readable but also machine-understandable.

EvoRecipes starts with a population of initial solutions (RDF encoded recipes) retrieved from *RecipeKG* [7]. It then selects the parent solutions and applies evolutionary operators (i.e. mutation, crossover) to generate offspring. The process of parent selection and evolution repeats for a certain number of iterations until the stopping criteria is met. The resultant solutions (RDF encoded recipes) are finally transformed into recipe text using the Davinci model of OpenAI GPT API. *EvoRecipes* comprises of number of components (such as initial population, selection, mutation, crossover and fitness function evaluation) that have been discussed in following subsections.

A. INITIAL POPULATION

We select the initial population of recipes from *RecipeKG* that has a collection of recipes stored in RDF format. *RecipeKG* is based on a 0.8M-Recipes dataset. The dataset comprises 0.8 million real human-generated recipes extracted from recipe websites.

B. SELECTION

We have used the roulette wheel as a population selection criterion in *EvoRecipes*. This is the fitness proportionate population selection criteria for reproduction as it gives a chance to individuals with low fitness value for being selected in the next generation along with more fit individuals. Hence it ensures population diversity by selecting individuals with varying fitness values.

C. MUTATION

Mutation replaces existing ingredients and actions in recipes with alternative choices that not only add diversity to the population but also improve the novelty. In *EvoRecipes* we

[7] https://github.com/HajiraJabeen/RecipeKG
[8] https://github.com/HajiraJabeen/RecipeKG/tree/main/0.8M-Recipes

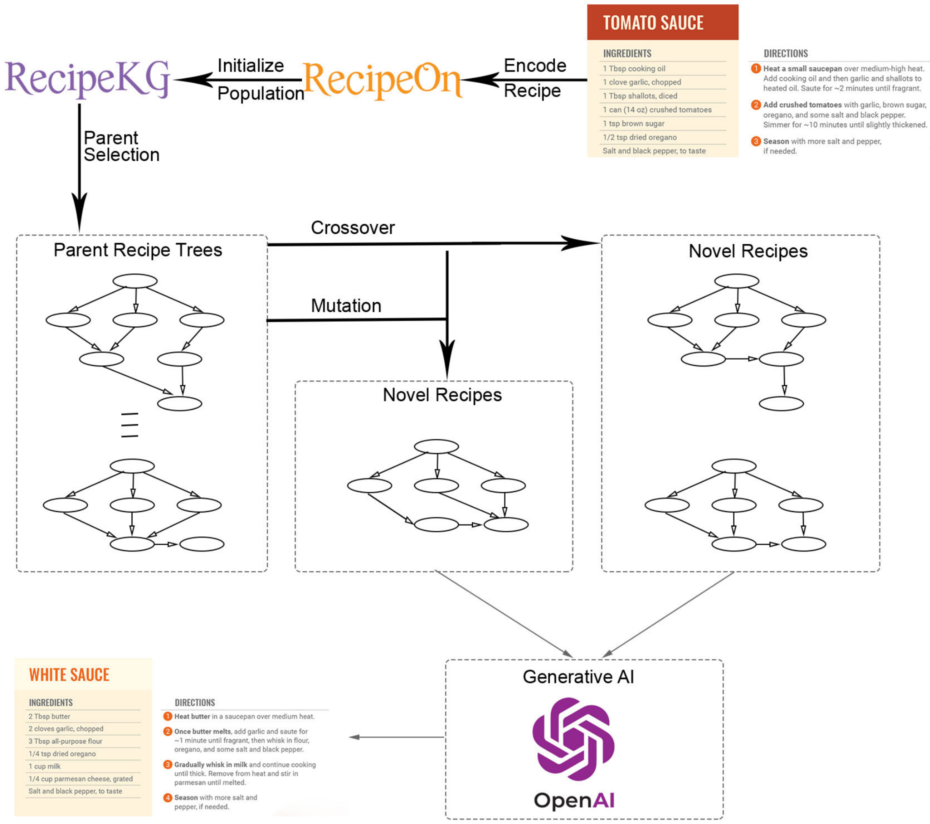


FIGURE 2. EvoRecipes framework generates new semantic-aware recipes (encoded in RDF format) using evolutionary operators and generates human-readable recipe text using Davinci model of OpenAI GPT API.

have proposed three mutation techniques that modify both ingredient and action nodes. These techniques have been discussed in detail in the following subsections.

1) INGREDIENT SUBSTITUTION

The ingredient is one of the key component of a recipe. It has a vital role in recipe preparation, taste, color, aroma, and presentation. Some ingredients have a primary role and are classified as *MainIngredients*, while others have a secondary role and are classified as *SideIngredient* or *FlavoringIngredient*. *RecipeOn* maintains an ingredient class hierarchy and divides ingredients into 12 classes and numerous sub-classes. Ingredient substitution replaces an ingredient i belonging to class c with another ingredient j that also belongs to the same class c. For example, nixtamal can be replaced with popcorn as both belong to the same corn class. Figure 3 shows the ingredients and their alternatives from four classes(i.e. rice, barley, corn, and grain types). Due to space limitations, we have not mentioned the remaining ingredient classes, however, their complete detail is available in *RecipeOn* ontology.

Figure 4 shows an ingredient substitution in which ‘‘fluffy microwave scrambled Eggs’’[9] (figure 4a) is mutated to generate a new recipe (figure 4b) by replacing milk with cheese.

[9]https://www.allrecipes.com/recipe/272293/fluffy-microwave-scrambled-eggs/

2) ACTION SUBSTITUTION

Same ingredients but different actions can lead to very different recipes. It impossible to prepare a food item without appropriate action details. *RecipeOn* divides *Action* class into three sub-classes (i.e. *Cooking*, *Preparatory*, and *PostCooking*). In the recipe evolution process, *EvoRecipes* replaces an action a_i with another action a_j using *RecipeOn*’s property *alternateAction*. It is mandatory that both a_i and a_j should belong to the same class c'. Detailed categorization of preparatory actions, cooking actions, and post-cooking actions are presented in figure 6, figure 7, and figure 8 respectively. Figure 6 shows the sixteen preparatory action categories. Each category has multiple options for replacement. Like for example chopping can be replaced with cutting or dicing. The action substitution operator generates different aroma, taste, and texture compared to the original recipe.

To explain action substitution using an example (noodle bowl[10] (figure 5a), we have replaced simmer with poach in mutated noodle bowl (figure 5b) recipe as shown in figure 5.

3) ACTION INTERCHANGE

Action interchange also introduce novelty in a recipe. Action substitution replaces an action with a potentially similar type of action whereas action interchange neither

[10]https://www.allrecipes.com/recipe/8493264/noodle-bowl-formula/

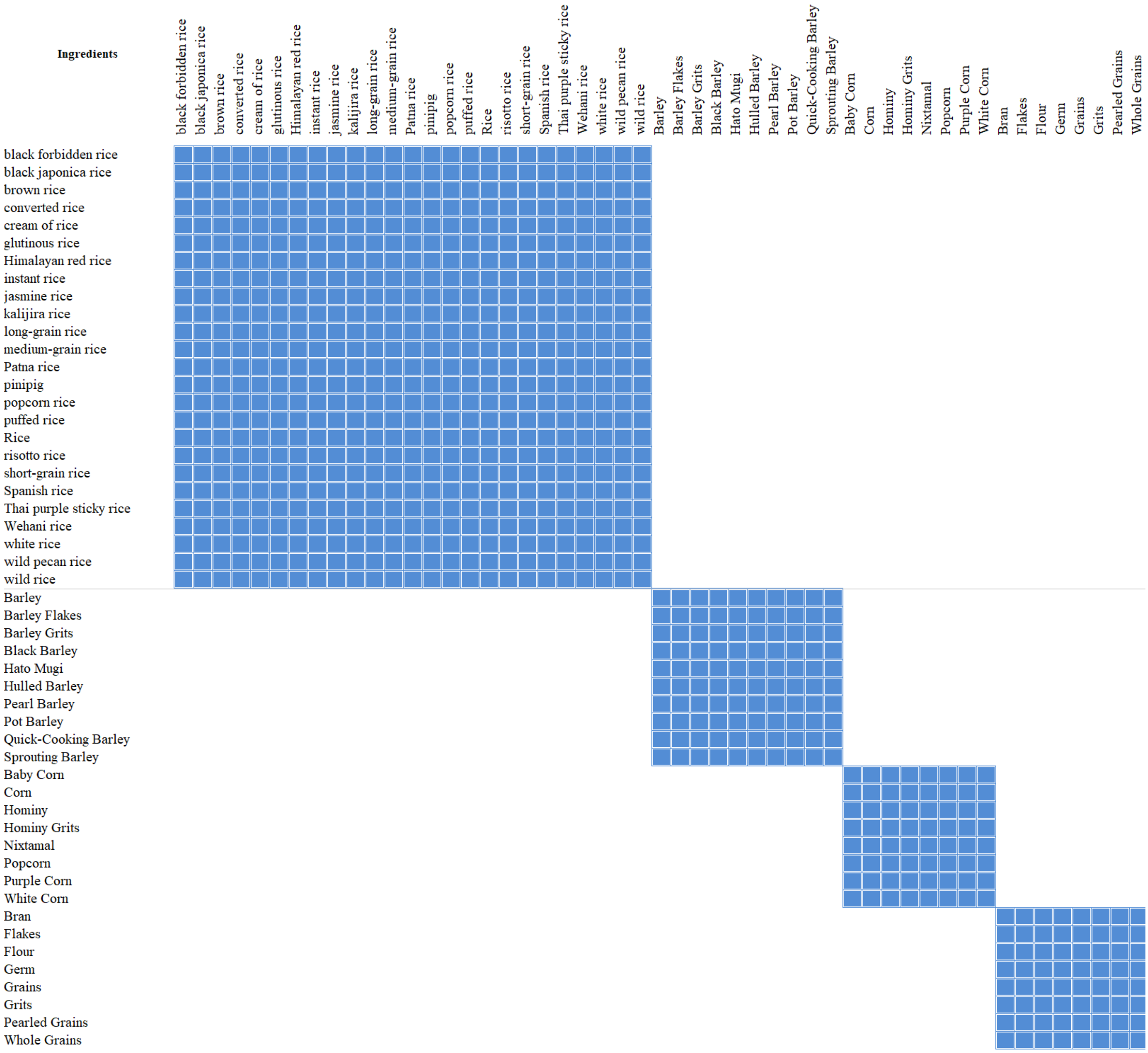
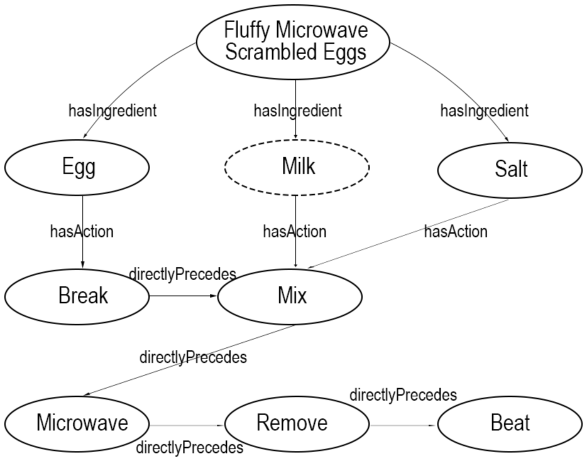


FIGURE 3. Alternative ingredient against four ingredient classes (i.e. rice, barley, corn, and grain types).

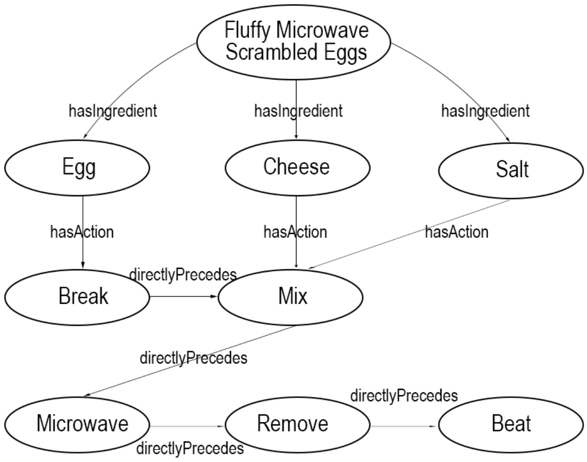
replaces any action nor adds any new action but just changes the sequence of existing actions. Let's suppose an action a_i *directlyPrecedes* a_j and a_j *directlyPrecedes* a_k then after action interchange a_i *directlyPrecedes* a_k and a_k *directlyPrecedes* a_j. It is mandatory that both a_j and a_k should belong to the same class. For example, grilling can interchange with toasting or browning as these three actions belong to the same class as shown in figure 7. Action interchange for noodle bowl recipe is shown in figure 5b in which seasoning is interchanged with topping.

D. CROSSOVER: PROCEDURE SUBSTITUTION

A procedure is a subset of a recipe that comprises a subset of related ingredients and actions. Let I be the set of ingredients and A be the set of actions in a recipe. Then a procedure P_j comprises of I_j ingredients and A_j actions such that $I_j \subseteq I$ and $A_j \subseteq A$. The alternative procedure is similar to the crossover operator in evolutionary algorithms. In the alternative procedure, we use the object property *alternativeProcedure* of *RecipeOn* ontology to replace a procedure P_i of a recipe r with procedure P_k of another recipe r'. The alternative procedure explores the recipe to a deeper extent and results



(a) Fluffy microwave scrambled eggs available at AllRecipes



(b) Mutated (milk substitution with cheese) fluffy microwave scrambled eggs

FIGURE 4. Mutation:Ingredient substitution example.

in a larger change to the recipe compared to the mutation operators.

To explain the crossover operator using an example we have selected two recipes (i.e. "Salmon in Sorrel Sauce"[11] & "Unadon"[12]) as parent recipes. "Salmon in Sorrel Sauce" comprises two procedures. Ingredients and actions involved in "prepare the sauce" and "prepare the salmon" procedures are shown in figure 9 using yellow-colored and green-colored nodes respectively. Similarly, two procedures "Unagi Sauce" and "Rice & Assembly" are shown in figure 10 using grey and blue colored nodes respectively for "Unadon" recipe. Figure 11 shows the novel recipe created by replacing the sauce procedure from "prepare the sauce" with "Unagi Sauce" in "Salmon in Sorrel Sauce" recipe. This alternative procedure results in a change of taste, aroma, and texture of the newly generated recipe.

[11]https://food52.com/recipes/4541-salmon-in-sorrel-sauce
[12]https://food52.com/recipes/31455-japanese-eel-rice-bowl-unadon

E. QUANTITATIVE EVALUATION OF RECIPE

Evaluation of a recipe is more of a subjective task, as it requires humans to assess the quality of a recipe based on taste, texture, aroma, and presentation style. However, to evaluate the alignment of a recipe with the intended goals, quantitative measures are also highly demanded. Each recipe is quantified based on multiple objectives/factors and finally aggregated to assign the fitness value (i.e. score) to a recipe. These quantifiable factors are discussed in detail in the following subsections.

1) NOVELTY

Novelty (λ) introduces a new combination of flavors, side ingredients, main ingredients, cooking actions, and cooking procedures during evolution that were not present in the initial recipe population. We have classified novelty in a recipe as (*i*) Novelty in ingredients; (*ii*) Novelty in actions.

Novelty in ingredients (equation 1) is useful for improving the quality of *EvoRecipe* generated recipes by incorporating unique combinations of ingredients.

$$\lambda_r^I = \frac{1}{N}\sum_{j=1}^{N}\frac{|I_r - I_j|}{|I_r|} \tag{1}$$

Here N represents the population size, I_r represents the set of ingredients in an evolved recipe r, and I_j represents the set of ingredients in a recipe j from the initial population. $I_r - I_j$ finds the set of ingredients in recipe r that are not present in recipe j.

Similarly, a novelty in actions (equation 2) is useful for improving the quality of evolved recipes by incorporating unique combinations of actions.

$$\lambda_r^A = \frac{1}{N}\sum_{j=1}^{N}\frac{|A_r - A_j|}{|A_r|} \tag{2}$$

Here A_r and A_j represent the set of actions in an evolved recipe r and the set of actions in a recipe j (from the initial population), respectively.

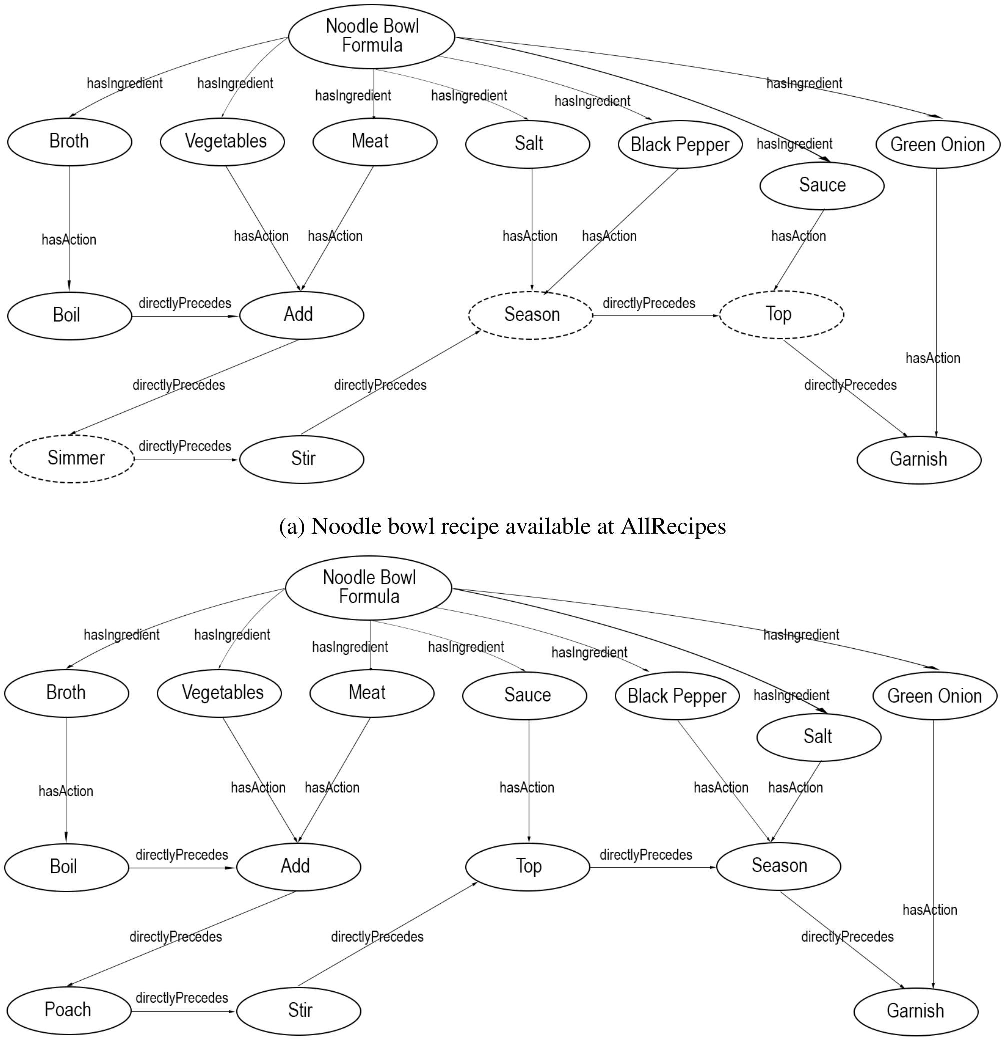
$$\lambda_r = \frac{\lambda_r^I + \lambda_r^A}{2} \tag{3}$$

The high value of λ_r represents a novel recipe, while a lower value represents a traditional recipe. We have mapped the value of λ_r in equation 3 in the range of 0 to 1 by taking the average of λ_r^I and λ_r^A.

2) SIMPLICITY

Simplicity (Θ_r) refers to the easiness involved in preparing a recipe. A simple recipe requires a small number of ingredients, a limited set of preparatory actions, and a small number of sequential steps. We have defined the equation 4 to measure the simplicity of a recipe. The high value of Θ_r represents a simple recipe, while the lower value represents a complex recipe.

$$\Theta_r = \frac{1}{|I_r| + 2.|A_r^{prep}| + |A_r^{cook}| + |A_r^{post}| + d_r} \tag{4}$$



(a) Noodle bowl recipe available at AllRecipes

(b) Mutated (action substitution & action interchanged) Noodle Bowl Formula

FIGURE 5. Mutation: action substitution and action interchange example.

Here $|A_r^{prep}|$,$|A_r^{cook}|$, and $|A_r^{post}|$ represent the number of preparatory actions, number of cooking actions, and number of post cooking actions respectively. While d_r refers to the height of a recipe tree. A high value of d_r contributes to a large number of sequential steps. A significant factor that contributes to the recipe simplicity is the number of preparatory actions. A simple recipe has less preparatory actions while a complex recipes requires more preparation before cooking actions. To discourage more number of preparatory actions in recipes we have assigned double weight to the reciprocal of A_r^{prep}.

3) VISUAL APPEAL

A visually appealing recipe (ζ_r) simulates the appetite and makes the dining experience more enjoyable and memorable. There are a variety of finishing actions(a subset of post cooking actions) that contribute to the visual appearance of a recipe. We have proposed equation 5, to measure the visual appeal of a recipe.

$$\zeta_r = \frac{|A_r^{fin}|}{|A_r^{post}| + \epsilon} \tag{5}$$

Here A_r^{fin} and A_r^{post} represent the number of finishing actions(such as garnishing, sprinkling, topping) and post-cooking actions used in a recipe r. while ϵ is a small positive value that avoids a division by zero in equation 5 when a recipe does not have any post-cooking action. ζ_r reflects the ratio of finishing actions to post cooking actions. A highly appealing recipe would have more concentration on finishing actions than post cooking actions.

4) FEASIBILITY

A feasible recipe (Υ_r) comprises of preferable ingredients & actions, and avoids undesirable ingredients & actions as

FIGURE 6. Categorization of preparatory actions for alternative action (mutation).

specified by the user. This preference can be based on the availability of ingredients, health conditions, and diet consciousness. We have defined the equation 6 to measure the feasibility of a recipe.

$$\Upsilon_r = \frac{|I_r^{des}| - |I_r^{undes}|}{2.|I_r|} + \frac{|A_r^{des}| - |A_r^{undes}|}{2.|A_r|} \tag{6}$$

Here I_r^{des}, I_r^{undes}, A_r^{des}, and A_r^{undes} represent the number of desired and undesired ingredients and actions respectively. Here Υ_r is the normalized sum of the score that encourages the desired actions and ingredients while punishing the undesirable ingredients and actions.

5) FITNESS FUNCTION OF A RECIPE (f)

The fitness of a recipe is compiled based on the score calculated in the above mentioned factors using equations 3, 4, 5, and 6. We have defined equation 7 to accumulate the fitness of a recipe that is based on novelty(λ), simplicity(Θ), visual appeal(ζ), and feasibility (Υ). In equation 7 we have summed up the factors that contributes to the fitness of a recipe. Here we have multiplied the feasibility factor as it is an important factor while calculating the fitness score of a recipe. Feasibility reflects the recipes alignment with user preferences. if a recipe is novel, simple, and visual appealing but not feasible then this would result in minimum fitness value. Moreover, w_1, w_2, and w_3 are the weighted values that give weightage to the novelty, visual appeal, feasibility, and simplicity based on user choices.

$$f = (w_1.\lambda_r + w_2.\zeta_r + w_3.\Theta_r).\Upsilon_r \tag{7}$$

F. RECIPE RDF TO RECIPE TEXT USING GENERATIVE AI

Novel recipes generated from *EvoRecipe* are in RDF format. Recipe RDF comprises classes (i.e. Ingredient, Action, Procedure, Author, AggregateRating, Nutrition, etc) and relationships (i.e. hasAction, hasIngredient, hasProcedure, directlyPrecedes) between the classes or literals. Although the novel recipes are machine understandable but lacks

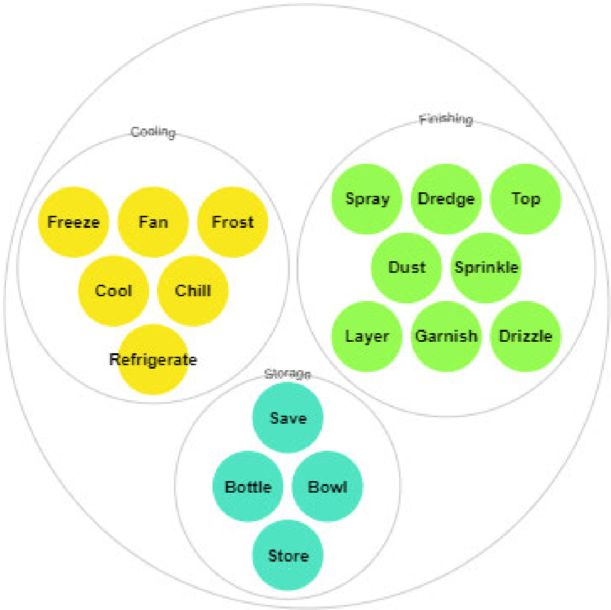


FIGURE 7. Categorization of cooking actions for alternative action (mutation).

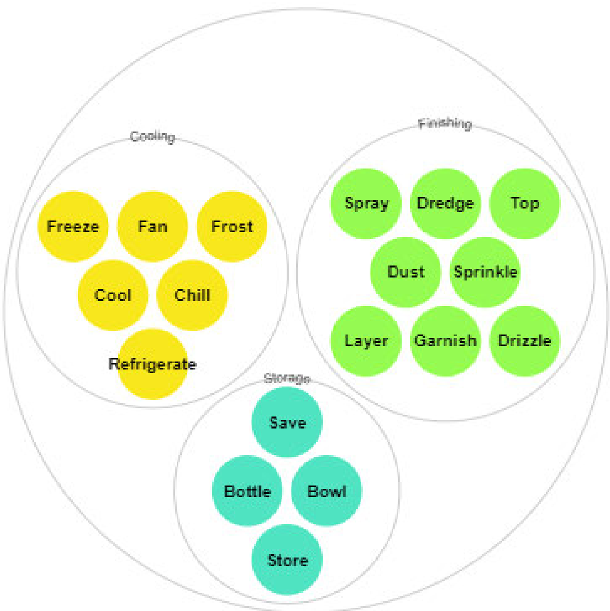


FIGURE 8. Categorization of post-cooking actions for alternative action (mutation).

human readability. Therefore, a model was needed that could map the recipe facts to human-readable statements. For this purpose, we have used OpenAI GPT API[13] (Davinci model) to create prompts that translate RDF facts to recipe ingredients and instruction statements. Listing 1 shows a recipe text generated using OpenAI GPT API against a novel recipe generated by *EvoRecipes*. The prompt corresponding to the generated recipe text was based on RDF format.[14]

```
Recipe: Pan—Fried Lamb Chops With Minted
        Pea Salad
Ingredients:
— 4 lamb chops
— 2 tablespoons brown sugar
— Salt to taste
— 1 teaspoon dried basil
— 2 tablespoons grape seed oil
— 1 teaspoon garlic powder
— 2 tablespoons distilled white vinegar
— 1 teaspoon garam masala
— 4 Thai chile peppers, thinly sliced
— 1 cup sugar snap peas
Instructions:
1. Heat the lamb chops in a pan with the
   lamb drippings.
2. Coat the lamb chops with the brown
   sugar, salt, and dried basil.
3. Saute the lamb chops in the grape
   seed oil.
4. Add the garlic powder, distilled
   white vinegar, garam masala,
   and Thai chile peppers.
5. Place the lamb chops on a plate.
6. Season the sugar snap peas with salt.
7. Cook the sugar snap peas in a pan.
8. Sprinkle the sugar snap peas with
   garlic powder.
9. Pull the sugar snap peas off the heat.
10. Serve the lamb chops with the
    minted pea salad.
```

Listing 1. Recipe text generated using OpenAI GPT.

V. QUALITATIVE RECIPE EVALUATION

To evaluate our novel recipe generation approach, we also performed a qualitative study on *EvoRecipes*. This evaluation has been carried out in a multitude of dimensions, including contextual evaluation, procedural evaluation, and novelty evaluation. Contextual metrics evaluates (taste, edible, ingredient combination, and action sequence metrics) that fulfills the user preferences. The procedural evaluation focuses on clarity and accuracy to understand the steps involved in a recipe. Recipe validity, complexity, and consistency metrics are covered under this category. Finally, novelty metrics not only evaluate the contribution of evolutionary operators in generating novel recipes but also investigate the quality of generated recipes. The metrics include unusual ingredient combinations, valid action substitution, and valid procedure substitution.

[13]https://colab.research.google.com/drive/1yMppDHGs8D0DBP4rw9PFieExUv9q4u54?usp=sharing

[14]https://github.com/HajiraJabeen/EvoRecipesOntology/blob/main/prompts/rdf2text

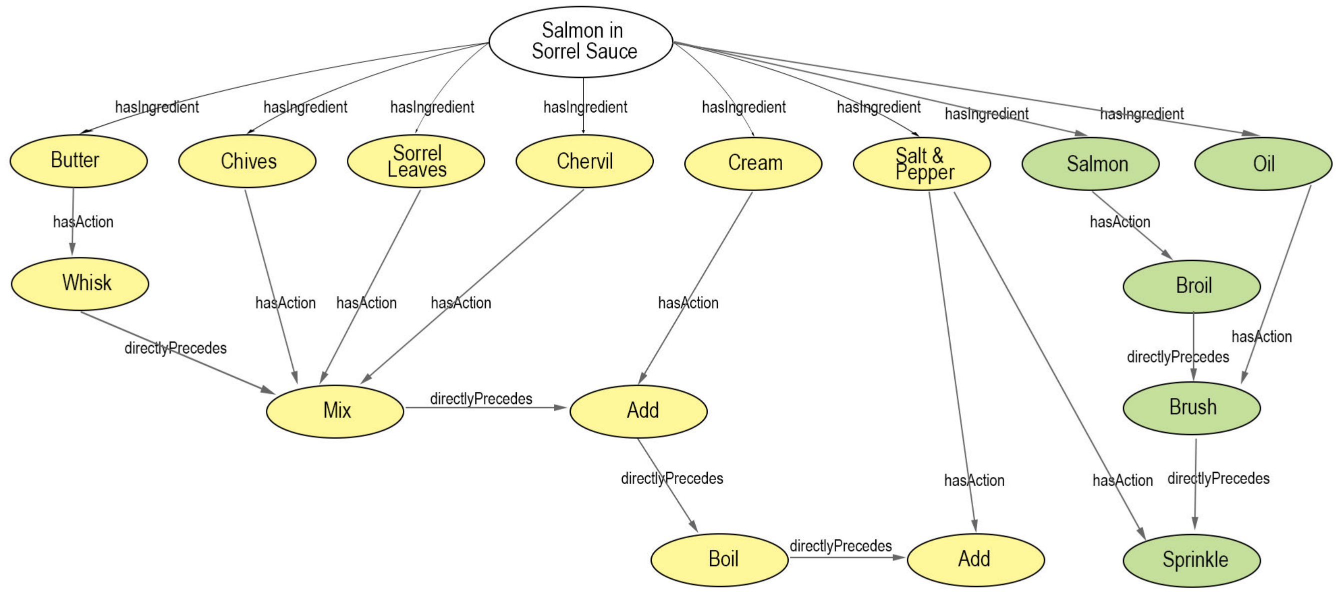


FIGURE 9. First parent recipe (i.e. Salmon in Sorrel Sauce[11]) comprising two procedures("prepare the sauce" and "prepare the salmon"). Ingredients and actions involved in "prepare the sauce" are shown using yellow colored nodes while "prepare the salmon" is represented using green colored nodes.

The quality of each recipe is evaluated along three dimensions, i.e., contextual, procedural, and novelty. The metrics used for this multi-dimensional evaluation have been discussed in detail in the following sub-sections.

A. CONTEXTUAL METRICS

Contextual recipe evaluation ensures that a recipe is well-aligned with the goals of the intended audience. If some food enthusiasts want to try a new recipe with available ingredients, then a machine-generated recipe should not only be novel but should also be edible and should have a non-conflicting set of ingredients. We have used four contextual metrics to evaluate the quality of a recipe as discussed below.

Taste: The taste of a recipe is based on the appropriate combination of ingredients, their freshness, a suitable sequence of actions, and a balanced use of the flavoring & seasoning ingredients. The taste of a recipe is also based on the user's preference and may vary from person to person. Also they can set the flavoring ingredients according to the taste they want from the recipe.

Edible: This is a criterion used to find the food items that can be consumed without causing any harm or risk to a person's health. It ensures that the food item is suitable and safe for use. Edible recipes include ingredients that are suitable for consumption. Also, it includes actions (i.e., boiling, baking) that make these ingredients safe to consume by removing harmful bacteria and parasites. In addition to safety, edible recipes should also provide suitable taste, aroma, and texture for a pleasurable eating experience.

Combination of ingredients: This is an important factor in cooking recipes as it influences texture, aroma, and flavor. A suitable and balanced combination of ingredients can make food delicious and visually appealing, and enjoyable. On the other hand, a poor combination can make food non-delicious and unappetizing. The reasons include combining ingredients with strong and conflicting flavors or combining ingredients with similar colors or textures that create a monotone and dull look. Thus the right combination of ingredients can make food delicious, enjoyable, and memorable.

Sequence of actions: Sequence of actions is also important to create well-balanced recipes. Two similar set of actions but with different sequences can generate food items that would have different textures, flavors, tastes, appearances, and presentations. The sequence of action also affects the cooking time of a recipe, e.g. adding parboiled ingredients helps in reducing the overall cooking time as compared to unboiled ingredients. The sequence of actions affects the interaction of ingredients (e.g. adding lemon juice too early in a recipe can discolor the texture of a vegetable). Some ingredients complement other ingredients while some ingredients conflict with each other. Therefore the compatibility of ingredients is also based on the right sequence of actions. Lastly food safety perspective is also considered in the right sequence of actions. For example, it is important to cook meat thoroughly to kill harmful bacteria. Therefore beef should be added earlier in a recipe than other ingredients to ensure that it imposes no health risks. Understanding the importance of a sequence of actions can help to generate food items that are safe, tasty, and visually appealing.

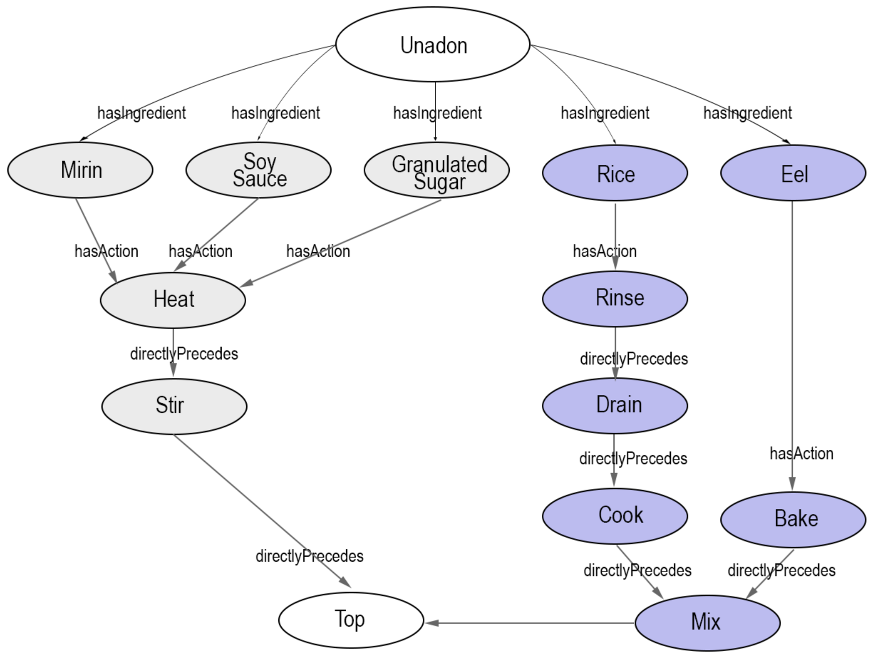


FIGURE 10. Second parent recipe (i.e. Unadon[12]) recipe comprising two procedures ("Unagi Sauce" and "Rice & Assembly"). Ingredients and actions involved in "Unagi Sauce" are shown using grey colored nodes while "Rice & Assembly" is represented using blue colored nodes.

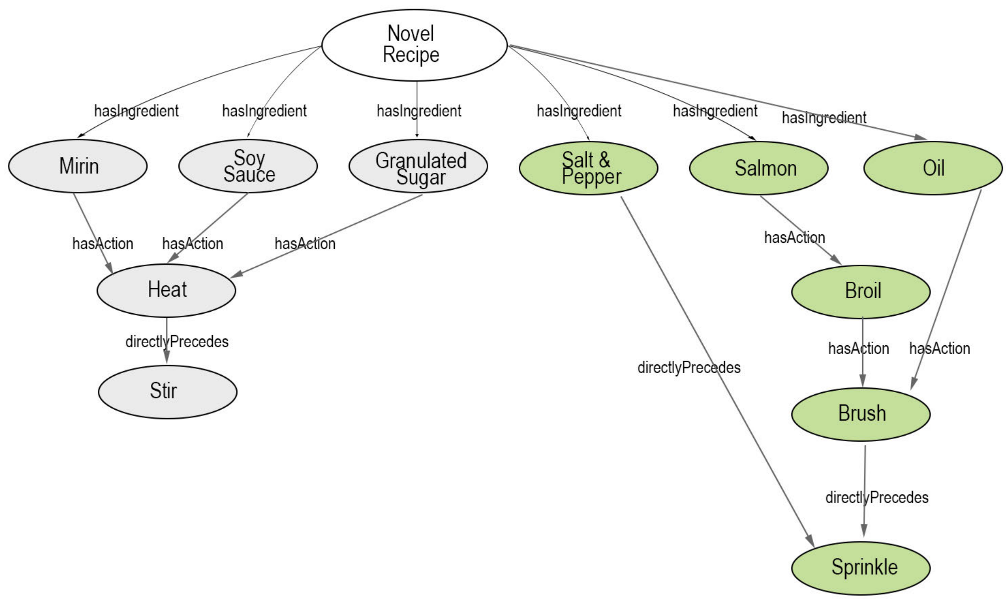


FIGURE 11. Novel offspring recipe comprising two procedures ("Unagi Sauce" and "Prepare the Salmon"). Ingredients and actions involved in "Unagi Sauce" are shown using grey colored nodes while "Prepare the Salmon" is represented using green colored nodes.

B. PROCEDURAL METRICS

Procedural metrics evaluate the clarity of steps involved in a recipe. It also assures that the steps are easy to understand and follow. These metrics are discussed in detail as follows.

Validity: Validity ensures that a recipe is comprised of a clear, unambiguous, and concise set of instructions along with an appropriate sequence of actions. Moreover, it has a detailed list of ingredients, quantities of ingredients, and reasonable steps related to preparation, cooking, and post-cooking actions.

Complexity: Complexity refers to the level of difficulty in following the step-by-step instructions of a recipe. The goal of this metric is to ensure that the recipe can be followed by the reader with a reasonable level of cooking experience and skill to create a food item that is consistent with the intended outcome. Professional cooks often conduct complexity evaluations to ensure that the recipes are well-written and understandable. Complexity arises due to inconsistencies, gaps, and ambiguities that lead to confusion during preparation. Overall a recipe should be easy to understand and follow.

Usability: Usability refers to the ease with which a recipe can be prepared by cooks with varying level of skills and experience. It is based on the factors like availability of ingredients, accessibility of equipment, and overall user-friendliness of the recipe. A recipe with poor usability requires specialized equipment, ingredients with low availability, and skills that are beyond the skill set of many cooks. Usability ensures that the recipes can be successfully prepared by a wide range of cooks.

C. NOVELTY METRICS

Novelty evaluation determines whether a recipe offers a unique or creative approach to a food item or floats an entirely new idea that hasn't been explored previously. It measures the originality or creativity of *EvoRecipe* generated recipes. Practically, novelty evaluation for computational creative culinary recipes involves comparing newly generated recipes with a large corpus of cooking recipes. An alternative to this approach is to get novel recipes assessed by human tasters. This evaluation helps to identify novel and unique recipes ideas that may have been unexplored or overlooked previously. We suggest three novelty evaluation parameters to asses the originality or uniqueness of a recipe as discussed below.

Unusual ingredient combination: The unusual combination of ingredients metric is helpful in crediting recipes that have a rare combination of ingredients (i.e. not available commonly in human-generated recipes). A rare ingredient combination will lead to recipes that would be very different in their taste, aroma, visual appearance, and texture. Hence leading to more novel recipes.

Rare Action Substitution: A recipe comprises preparatory actions, cooking actions, and post-cooking actions. Alternative actions consider how unique or unusual preparatory actions and cooking actions have been used in a recipe compared to other similar recipes. If a machine-generated recipe applies more unique cooking actions on available ingredients then it would be considered more novel compared to a recipe that applies more traditional actions on ingredients.

Rare Procedure Substitution: A procedure or sub-recipe (component recipe within a main recipe) is a subset of a recipe that involves ingredients and corresponding cooking actions. This metric assesses the novelty of a recipe based on the usage of unique or new procedures within a recipe. If a machine-generated recipe introduces a unique sauce procedure or replaces a traditional sauce sub-recipe with an unusual sauce sub-recipe then it is considered more novel compared to a recipe that replaces a procedure with another commonly used procedure. This evaluation technique helps to find more unique sub-recipes that have not been used before with similar recipes and discourages finding commonly used sub-procedures with similar recipes.

D. SURVEY AND ANALYSIS

To evaluate the qualitative metric of *EvoRecipes* approach, we have conducted a qualitative study. The study aims to investigate the contribution of evolutionary operators (mutation & crossover) in generating novel recipes and the contribution of generative AI (OpenAI GPT) to convert those recipes into human-readable text. In addition, this study is helpful for evaluating the quality of *EvoRecipe* generated recipes.

To conduct the study we have used two recipes. The first recipe was chosen randomly from *RecipeKG* that reflects an original human-generated recipe from a recipe website, while the second recipe was generated using the *EvoRecipe* framework.

The quality of a culinary recipe is a subjective matter therefore we have designed a survey (using Google Forms) to ask participants to assess the quality of the floated recipes. The survey comprises 11 multiple choice questions (that is, at least one against each evaluation metric as described in sections V-A,V-B, and V-C) to be filled out by the participants. Each question follows a template (i.e. Which of the two recipes is/has <evaluation-metric>? e.g, Which of the two recipes is more usable?) with four options against each question (Recipe A, Recipe B, Both of them, None). The survey questions are listed below.

1) Which of the two recipes is edible?
2) Which of the two recipes is valid?
3) Which of the two recipes is complex?
4) Which of the two recipes has an appropriate ingredient combination?
5) Which of the two recipes has unusual ingredient combinations?
6) Which of the two recipes has the appropriate sequence of instructions?
7) Which of the two recipes has rare actions/instructions?
8) Which of the two recipes has a rare procedure?
9) Which of the two recipes is more tasty?
10) Which of the two recipes is prepared easily?
11) Which of the two recipes is more readable?

The survey is filled out by 24 users and the results are presented in table 1. The results show that the *EvoRecipe* generated recipes are more usable (13 users recommended *EvoRecipe* generated recipes where as 9 users recommended human-generated recipes), readable (12 users recommended *EvoRecipe* generated recipes where as 9 users recommended human-generated recipes), having unusual ingredient combination (11 users recommended *EvoRecipe* generated recipes where as 6 users recommended human-generated recipes),

TABLE 1. Recipe evaluation comparing Human-generated recipe with EvoRecipe generated recipe.

Evaluation Metric	Human-generated Recipe	EvoRecipe generated Recipe	Both of them	None
Taste	09	**10**	03	02
Edible	04	07	**14**	-
Appropriate Combination of Ingredient	**13**	07	04	01
Sequence of Action	08	06	**09**	02
Validity	05	04	**14**	01
Complexity	**13**	10	-	01
Usability	09	**13**	03	-
Unusual Ingredient Combination	06	**11**	01	06
Rare Action Substitution	06	**08**	03	07
Rare Procedure Substitution	**09**	**09**	01	05
Readable	09	**12**	04	-

rare action substitution (8 users recommended *EvoRecipe* generated recipes where as 6 users recommended human-generated recipes), simple (10 users rated *EvoRecipe* generated recipes as complex recipe where as 13 users rated human-generated recipes as a complex recipe), and tasty (10 users recommended *EvoRecipe* generated recipes where as 9 users recommended human-generated recipes) than human generated recipe. Moreover, both recipes are valid (14 users recommended *EvoRecipe* generated recipes and human-generated recipes) and having appropriate sequence of actions (09 users recommended *EvoRecipe* generated recipes and human-generated recipes). *EvoRecipe* performed better in 07 qualitative metric (Taste, Edible, Usability, simplicity, Unusual ingredient combination, rare action substitution and readable) equal in 1 that is rare procedure substitution as compared to human-generated recipes.

VI. RESULT AND DISCUSSION

A. EXPERIMENTAL SETUP

We have performed experiments on Google Colab using Python 3 Google Compute Engine with 12 GB Ram and 107 GB secondary storage. We have selected an initial population of 100 recipes from RecipeKG as a sample to evolve the recipes. This population comprises lamb recipes, poultry recipes, rice recipes, and Asian noodle recipes that has lamb, poultry, rice, and Asian noodles as the main ingredient respectively.

To evolve the recipes we have implemented Genetic Algorithm [15] in python. With respect to parameter settings single mutation of either ingredient or action node is performed for each recipe. Parent recipes for crossover are selected using tournament selection with a crossover rate of 0.5. Roulette wheel has been used for next generation's population selection while the stopping criteria is 35 generations. These parameter values were taken from autochef [3].

B. EXPERIMENTS

EvoRecipes has been executed 10 times to get the average metrics values (novelty, simplicity, visual appeal, and fitness) as shown in figure 12, figure 13, figure 14, and figure 15 respectively. These figures presented the results of quantitative evaluation of recipes generated through *EvoRecipe*. Figure 12 shows the continuous improvement of novelty for all four type of recipes. Mutation dominate crossover in novelty improvement due to the reason that crossover just incorporates new ingredients/actions that are available in other recipes of the current population, while mutation incorporates new ingredients and actions from *RecipeOn* ontology that are not even available in the population. Hence mutation generates unusual/unique ingredient and action combination. The value of novelty (λ_r) is calculated using equation 3 and represents an unusual ingredient combination and varying actions in a novel recipe compared to the set of ingredients and actions in initial population. Figure 12 shows that Asian noodles have slightly less novelty value compared to lamb, poultry, and rice recipes. This is due to the fact that ingredients involved in Asian noodles have limited alternative options and restricts to incorporate unusual ingredient combinations.

Figure 13 shows that Asian noodles recipes are more simple to make as they involve lesser number of ingredients and few preparatory actions, while lamb recipes are more complex as it generally involves more number of ingredients and actions. However poultry and rice recipes are simpler than lamb recipes while complex than Asian noodles recipes. The simplicity (Θ_r) of a recipe is calculated using equation 4 and is generally an over-looked factor. A simpler recipe is not only easy to remember (due to limited number of ingredients and actions) but also requires less amount of effort to prepare a food item.

Figure 14 shows that poultry, rice, and lamb recipes are more visually appealing compared to Asian noodle recipes. Poultry, rice, and lamb recipes have more finishing actions (i.e. garnishing, topping, layering, drizzling) that help to improve their visual appeal. While Asian noodles have a low average visual appeal score because they have limited finishing actions. Figure 14 shows the Visual Appeal (ζ_r) score calculated through equation 5, for the newly generated recipes through *EvoRecipe*. Poultry, Rice and Lamb recipes have more visual appeal score than noodle recipes as they have more finishing actions that makes a recipe visually appealing.

[15]https://github.com/HajiraJabeen/EvoRecipesOntology/blob/main/EvoRecipes/EvoRecipes.py

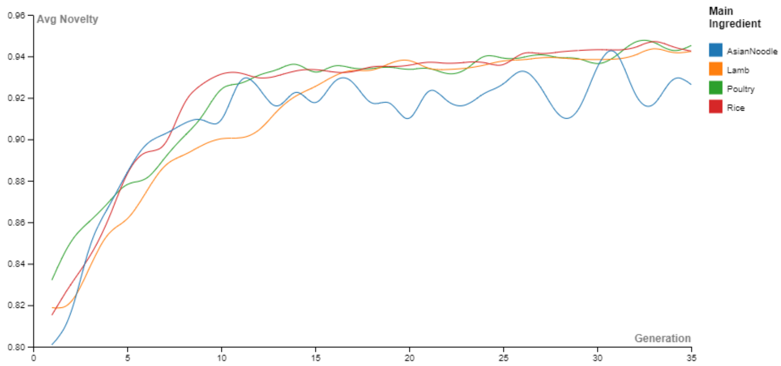


FIGURE 12. Average novelty over 10 runs of *EvoRecipes*.

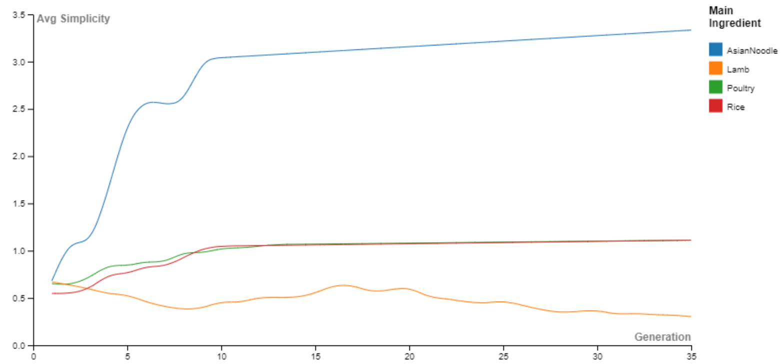


FIGURE 13. Average simplicity over 10 runs of *EvoRecipes*.

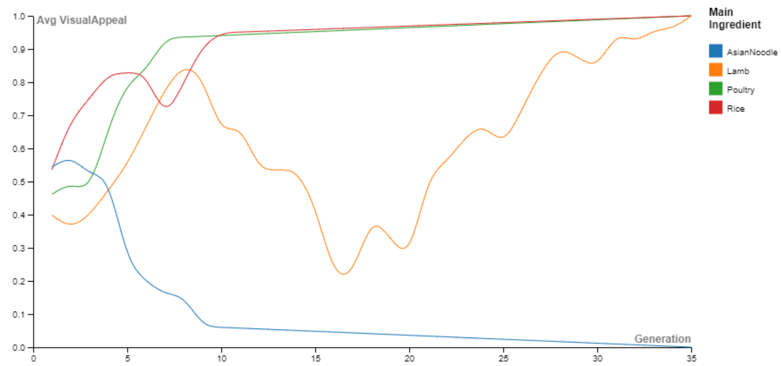


FIGURE 14. Average visual appeal over 10 runs of *EvoRecipes*.

The average fitness score (f) of novel poultry, lamb, rice, and Asian noodle recipes (generated through *EvoRecipe*) is shown in figure 15. f has been calculated using equation 7. Asian noodles have high fitness values compared to poultry, rice, and lamb recipes. This is due to the reason that Asian noodle recipes are simpler than counterpart recipes while in terms of novelty, Asian noodle recipes are closer to the fitness value of lamb, poultry, and rice. While poultry and rice recipes have similar fitness values across many generations as they have close values of novelty, simplicity, and visual appeal across many generations. Lamb recipes shows less fitness score (f) value as they are complex and have less visual appeal as compared to poultry, rice, and noodle recipes. Results in Figures 12, 13, 14, and figure 15 proves that recipes generated using *EvoRecipes* are novel, simple, visually appealing, and valid.

C. COMPARISON WITH RECIPE EVOLUTION TECHNIQUES

EvoChef [33], and AutoChef [3] have used genetic algorithm and genetic programming respectively to evolve the recipes. EvoChef has only covered the limited potatoe recipes and has lacked in defining fitness function for recipe evaluation.

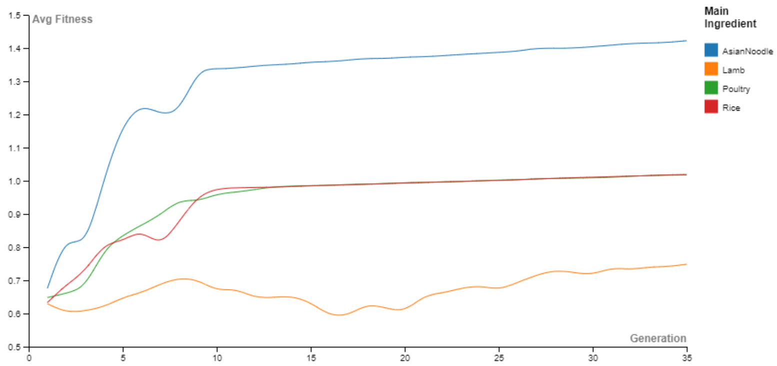


FIGURE 15. Average fitness value over 10 runs of *EvoRecipes*.

They have evaluated recipes manually by human expert. While AutoChef has used genetic programming to evolve the recipes. They have tried with limited food replacement options, and few action replacement options. They are also not taking care of sequencing of instructions and actions while performing recipe evolution. Moreover they are not using context aware machine understandable recipes. However *EvoRecipes* is based on the schema of *RecipeOn* ontology that encodes rich information related to a recipe. It represents the recipe as a process and includes ingredients, actions, nutrition, and sequence of actions. Furthermore *EvoRecipes* evolve recipes by applying ingredient substitution, action substitution, action interchange, and procedure substitution while using the semantically rich schema of *RecipeOn* ontology. The ontology provides support to *EvoRecipe* in valid substitution of ingredients and actions using rich recipe knowledge, class hierarchy detail of ingredients & actions, and sequence of actions. Also *EvoRecipe* ensures the valid procedure substitution while evolving the recipe as it uses the alternative procedure rules defined by the *RecipeOn* ontology. *EvoRecipe* ensures the quantitative evaluation of recipe of through its proposed fitness function and qualitative evaluation of recipe through its proposed multi-perspective metrics.

VII. CONCLUSION

In this article, we have proposed the recipe evolution framework *EvoRecipes* that randomly selects the initial population from *RecipeKG* knowledge graph. *EvoRecipes* uses *RecipeOn* ontology to mutate the recipes using three different mutation operators (i.e. ingredient substitution, action substitution, and action interchange). Moreover in procedure substitution it interchanges the procedures of two selected recipes (through tournament selection) to perform the crossover operation. Finally, for the newly created recipes, we have generated the human-readable recipe text using OpenAI GPT API (Davinci model). Also we have proposed a quantitative metrics that contribute to the fitness evaluation of a recipe. Furthermore, we have carried out a qualitative study using the survey to evaluate the subjective parameters (like taste, edible, complexity, usability, novelty etc.) of a recipe. Currently *EvoRecipes* do not take care of the nutritional details while evolving recipes.

VIII. FUTURE WORK

In the future, we will extend evaluation metrics and to tune the parameters that are involved in recipe evolution. Also we aim to explore the distributed in-memory computational frameworks (like Apache Spark, Apache Flink) to speedup the recipe evolution process and to increase the scalability of *EvoRecipe* framework.

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