CREATING EUROPEAN FOODOME KNOWLEDGE GRAPH TO CAPTURE THE DARK MATTER OF NUTRITION

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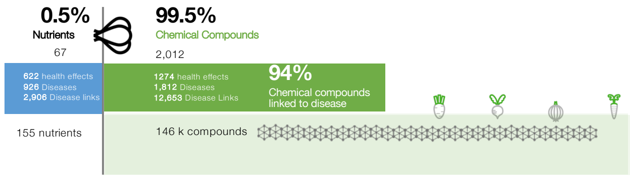
INTRODUCTION

- A significant part of global public health problems can be traced back to environmental and lifestyle factors.
- Our current understanding of the way food molecules affect health is largely limited to a few hundred components tracked by food composition databases.
- Yet, **these components represent only a tiny fraction of the total composition of the food supply**, hindering research from discovering mechanistic effects and roles of food molecules.
- **To solve this problem, we have designed a Big Data and AI strategy for the creation of a high-resolution collection of food composition: Foodome (from food exposome)**

The Dark Matter of Nutrition



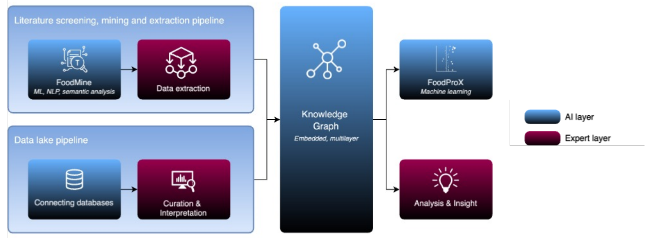
OBJECTIVES

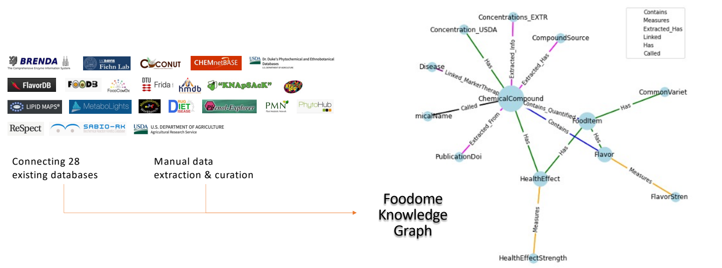
- US Foodome: technology, Nutritional Dark Matter (NDM) database
- AI revolution
- Bringing Foodome to the age of AI while extending to Europe
- Objective: **build a Knowledge Graph** and feed it with data
  - Find and rank relevant information and resources
  - Find relevant terms
  - Connect existing dataset
  - Develop a data lake where entities are connected

METHODS

- In this European pilot conducted in Hungary, data from **28 existing** food composition, biochemical, and health effect **databases were connected** and curated.
- An **AI-assisted pipeline (FoodMine)** was designed to complement the database curation, reviewing and extracting data from scientific literature for the 8 most relevant Hungarian food commodities.
- The resulting database was designed to **show the interplay between foods**, their **compounds**, and **potential downstream effects** of their consumption through a network science approach.

Foodome layers

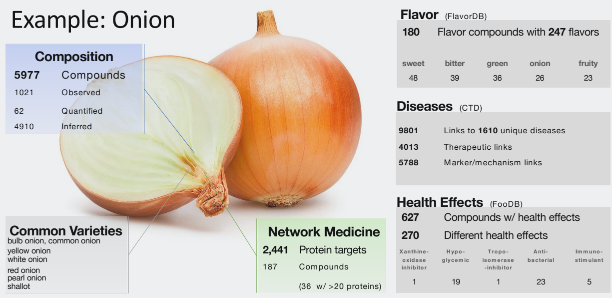




RESULTS

- A unified Hungarian **Foodome Knowledge Graph (FKG)** was created.
- The FKG contains ontologies of 10 different entity types (FoodItem, CommonVariety, ChemicalCompound, ChemicalName, Concentration, Flavor, FlavorStrength, Disease, HealthEffect, HealthEffectStrength) and 20 relationships (e.g., chemical-disease associations, food item-health effect associations).
- This pilot FKG alone contains **30k+ entities** and **100k+ relationships**, revealing connections between food compounds and potential mechanisms of action, both marker and therapeutic, and disease associations as well.

Example: Onion



IMPACT

Nutrition science: demonstrating that today's nutritional recommendations are not (or only partially) evidence-based
Example: Integrating recent advances of medical sciences

FoodAsDrug: Identify food molecules with beneficial health effects
Example: Mapping the health implications of 53 polyphenols

Food regulatory framework: developing new public health regulatory legislation
Example: Incentive system based on composition or health effects

Start-up ecosystems: agri-food, nutrition, health industry can all benefit from results
Example: Personalised evidence-based dietary app

Health science: developing nutritional guidelines and individual-targeted (personalized) nutrition applications
Example: Developing an app showing the processing level of foods

Food&Drug Intractions: Predict foods that alter the efficacy of specific drugs
Example: Why avocado decreases the effectiveness of Warfarin

Agri-food industry: enabling the development of functional/healthy/wholesome food products
Example: Development of functional foods based on health evidence

AI: demonstrating the applicability of cutting-edge AI technology in evidence generation
Example: AI-based relevance screening and data extraction

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