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Personalized Personality Insights and Growth Recommendations Based on User's Interests and Behaviours.

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Abstract-* In order to tackle the problem of more accurately and efficiently identifying modified information in media, this study presents the Roberta-LightGBM approach framework, which combines the advantages of Roberta and LightGBM. Using a natural language processing (NLP) our strategy seeks to quickly detect and reduce manipulated content using a machine learning technique in LightGBM and a language processing (NLP) model in Roberta. Compared to more conventional methods like BERT, which require far larger datasets for training across a variety of applications, the use of Roberta's NLP model allows for the effective training of large datasets in a short amount of time. In the modern era, the fast-paced evolution of industries and career landscapes has placed a premium on the ability of individuals to understand and leverage their skills effectively. However, traditional skill assessment methods, such as standardized personality tests or fixed-question surveys, often fail to capture the full spectrum of an individual's abilities. These assessments are typically static, generalized, and not tailored to a user's unique context or personal growth. As a result, they struggle to address the dynamic and multifaceted nature of human skills, especially those developed through hobbies and personal interests. This research proposes an innovative AI- based adaptive skill assessment system that overcomes these limitations by employing advanced natural language processing (NLP) and machine learning techniques. The system dynamically generates personalized questions in real-time, based on a user's input about their interests and activities. By continuously analyzing responses and adjusting content accordingly, it provides a tailored and evolving assessment experience. This adaptive approach allows the system to uncover hidden or transferable skills derived from hobbies and offer relevant feedback for both personal growth and career advancement. The key contributions of this research include the integration of NLP models like GPT-3 and BERT for question generation, the application of machine learning algorithms to map interests to skills, and the development of a feedback engine that offers actionable insights. The system's adaptability ensures that the assessment evolves alongside the user, making it a valuable tool for lifelong learning and professional development. By addressing the limitations of traditional assessment methods, this AI-driven model has the potential to transform how individuals and organizations approach skill identification and career planning.

I. INTRODUCTION

In the modern, rapidly evolving world, both individuals and organizations are increasingly focused on skills and competencies as the cornerstone of personal and professional development. Understanding one's strengths, areas for improvement, and untapped potential is crucial for success in various domains, from education to career planning. However, traditional assessment tools, such as personality tests or fixed-question surveys, have significant limitations in meeting the complex and dynamic needs of today's users.

Conventional assessments like the Myers- Briggs Type Indicator (MBTI) or DISC profiles offer a static snapshot of an individual's personality or skill set. These methods are not adaptive and fail to evolve alongside the user. Additionally, they tend to be generalized, often lacking the ability to provide deep insights that reflect an individual's personal context, interests, or unique combination of skills. This lack of customization and real-time adaptability leaves significant gaps in understanding one's true abilities, especially skills developed through hobbies and personal interests, which are often overlooked but can be highly transferable to real-world applications.

For instance, consider a person who engages in creative writing as a hobby. Traditional assessments might not recognize the critical thinking, problem-solving, or storytelling skills honed through this activity, skills that are valuable in various careers such as marketing, content strategy, or public relations. Similarly, individuals passionate about strategic games like chess might possess exceptional analytical and strategic thinking skills, but these are rarely identified in standard skill assessments. This highlights the need for a system that can dynamically interpret and adapt to a user's evolving interests and experiences.

II. PROBLEM STATEMENT

Despite the demand for better skill assessment tools, current solutions have three main shortcomings:

1. Lack of Personalization in Assessments: Traditional assessments use a one-size-fits- all approach that fails to consider the nuances of individual hobbies, interests, or evolving skills. The lack of tailored questions and adaptive mechanisms makes these tools less effective for meaningful skill evaluation.

2. Difficulty in Identifying Skills from Hobbies: Many individuals are unaware of how the skills they develop through personal interests can translate into professional strengths. Existing tools do not effectively map hobbies to valuable skills, creating a gap in self-awareness and career planning.

3. Limited Insights for Personal Growth and Career Development: Without adaptive, personalized feedback, users struggle to identify opportunities for growth and skill enhancement. This limits their ability to make informed decisions about their personal and professional trajectories.

III. OBJECTIVES

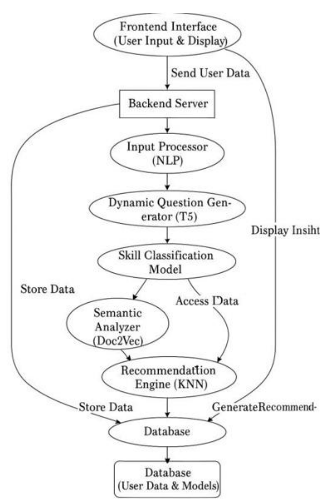
This research aims to address these challenges by developing an AI-based adaptive skill assessment system that uses natural language processing (NLP) and machine learning techniques. The primary objectives of the system are:

Designing an AI Model for Personalization: The system will dynamically generate personalized questions based on the user's hobbies and interests, ensuring relevance and engagement. This will be achieved using state-of-the-art NLP models capable of understanding and generating human-like text.

1. Mapping Skills to Interests Using AI: The system will interpret user-provided information on hobbies and map it to relevant skills using advanced machine learning algorithms. This approach will uncover hidden skills and demonstrate their applicability in real-world scenarios.

2. Providing Adaptive Feedback for Development: The system will continuously analyze user responses and offer personalized, actionable feedback. This will guide users on how to develop their skills further and explore new career opportunities, making the assessment process a valuable tool for lifelong learning.

System Architecture:



III. ALGORITHMS

1. App Initialization

1.Import all necessary libraries (Flask, MySQL, OAuth, Pandas, Pickle, etc.).
2. Initialize the Flask app with a secret key.
3.Configure email settings using Flask- Mail (optional).
4.Establish MySQL database connection using `mysql.connector`.
5.Load the CSV question dataset into a Pandas DataFrame.
6.Load pre-trained ML models:

- `skill_model.pkl`
- `career_model.pkl`
- `vectorizer.pkl`
- `mlb_skills.pkl`
- `mlb_careers.pkl.

2. User Authentication Flow

a. Google OAuth Login

- Route: `/login/google`
- Redirects the user to Google's
- OAuth consent screen.
- On success, redirects to
- `/callback/google`.
- Retrieves user details from Google and stores them in the database (if not already present).
- Saves user ID and name in the session.

b.Manual Login/Signup

- Routes: `/login` and `/signup`
- New users fill a form; details are stored in `users` table.
- Existing users log in with email/password.
- Upon success, session variables are initialized (`user_id`, `user_name`).

3. Interest Selection and Dynamic Question Generation

- Route: `/assessment`
- Displays 10 predefined interests (e.g., Coding, Drawing).
- On form submission (`/submit_interests`):

1.Retrieves the selected interests.
2.Filters the dataset to find 5 questions per interest.
3.Replaces `      ` in question text with the interest.
4.Randomizes and stores questions in the session (`questions`).
5.Initializes `q_index` and `answers` in session.

4. Question Answering Process

- Route: `/text_questions`
- Displays one question at a time from the session.
- User types an answer → it's stored in
- `session['answers']`.
- `q_index` is incremented.
- Repeats until all questions are answered.

5. Skill and Career Prediction

- Route: `/result`
- Step-by-step logic:

1.Retrieve `interests` and `answers` from session.

2.Text Preprocessing**:
Concatenate all interests and answers into one string.
Use `TfidfVectorizer` to transform the text into a numerical feature vector.

3. Model Prediction:
`skill_model.predict(X_input)` returns a binary array of predicted skill tags.
`career_model.predict(X_input)` returns a binary array of predicted career tags.
`mlb_skills.inverse_transform()` converts the binary array into a list of actual skill names.
`mlb_careers.inverse_transform()` does the same for career names.

4. Domain Inference:
If interest contains "Coding" or "Problem Solving", domain is labeled `Technology`.
Else, it's labeled `Creative`.

5. Database Storage:
Insert prediction results (`user_id`, `domain`, `skills`, `careers`) into

`user_results` table.

6. Session Update:
Store `predicted_skills` and `domain` in session for later use.

7. Result Rendering:
`result.html` shows domain, top skills, and suggested careers with a custom success messagel

6. Progress Tracking
Route: `/api/user-progress`

1. Retrieves the most recent result for the user from the `user_results` table.
2. Randomly generates a progress score (between 50%–95%) for each predicted skill.
3. Returns a JSON object of skills and their progress values

7. Additional Routes

- `/progress`: Renders a progress page showing a visual representation of the progress API data.
- `/learn`: Placeholder for future learning content or skill development links.
- `/restart_assessment`: Clears session data related to assessment and redirects to interest selection.
- `/logout`: Clears the session and logs the user out

8. Machine Learning Model Training (Offline)
Not part of Flask code but essential for understanding the ML part:

- Collected a dataset with user interests + answers → labeled with skills and careers.
- Preprocessed text using
- `TfidfVectorizer` to convert to numeric form.
- Applied multi-label classification using algorithms like:
- `RandomForestClassifier`
- `LogisticRegression`
- With `OneVsRestClassifier` or `MultiOutputClassifier`
- Used `MultiLabelBinarizer` to encode multiple skills and careers as binary vectors.
- Trained models saved using `pickle` for loading into Flask app

Models used in the project:

1.T5(Text-to-TextTransfer Transformer)
- Example Flow:

Input: "Generate 5 questions about the user's skills in 'Coding'"
→ Output: ["How do you usually approach debugging?", "Describe a time when you built a complete application."]

2. BERT(Bidirectional Encoder Representations from Transformers)
- Example:

Answer: "I usually create wireframes in Figma before moving to frontend code."
→Extracted skills: "UI/UX Design", "Figma", "Frontend Development"

3.Skill Classification Model (Random Forest / Decision Tree or Custom SVM Classifier)
- Training Data Example:

Keywords,Skill Domain
"React, Figma, HTML, CSS",Web Development
"TensorFlow, Data, Model",Machine Learning.

4.Doc2Vec / Word2Vec Embedding Model (optional/advanced)
- Use Case:

Helps in fine-grained skill prediction especially when vocabulary varies (e.g., “made an app” vs. “developed a mobile solution”)

5. KNN (K-Nearest Neighbors) Recommender for Growth Suggestions

Workflow Summary of Model Usage:
1. User logs in → Selects interests/hobbies.
2. T5 Model → Generates 5 open- ended questions.
3. User enters answers.
4. BERT → Extracts meaningful skills from answers.
5. Classifier (Random Forest/SVM) → Maps to domains + predicts skills.
6. Optional: Doc2Vec → Refines understanding of answers.
7. KNN → Suggests further learning paths and career areas.

8. Final Output → Skill domain, Skill list, Recommendations.

Why This Works Without Binary Inputs:
Subjective inputs offer depth and personalization.

- Transformers (T5, BERT) are ideal for natural language understanding and generation.
- The use of semantic parsing and vector-based analysis enables your system to:
- Understand intention and expertise.
- Go beyond simple "yes/no"
- checks.
- Provide rich, user-specific insights and guidance.

CONCLUSION

The AI-based dynamic skill assessment model outlined in this paper presents a cutting-edge approach to personalized learning and skill evaluation. By leveraging advanced technologies such as Natural Language Processing (NLP), Machine Learning (ML), and Deep Learning (DL), the system offers a dynamic, adaptive, and interactive platform for assessing user skills across a wide range of domains.

The system operates in a feedback- driven loop where it continuously adapts to the user's performance, dynamically adjusting the difficulty and relevance of questions based on their responses, skill level, and learning progress. Through the User Profile and Data Collection Module, the system gathers valuable data on the user's historical responses, time taken to answer, and accuracy, building a robust profile that informs the question generation process.
The NLP Engine plays a pivotal role in understanding user inputs and generating grammatically correct, contextually relevant questions. It utilizes techniques like Named Entity Recognition (NER), Sentence Parsing, and Semantic Understanding through

state-of-the-art models like BERT and GPT. These models enable the system to generate follow-up questions and adapt in real time to the user's expertise.

The Machine Learning Engine integrates algorithms like Clustering (e.g., K-Means) and Reinforcement Learning (RL) to track user progress, classify their skill level, and adjust the complexity of questions dynamically. By segmenting users into clusters based on performance, the system can deliver tailored assessments that are neither too easy nor too difficult, promoting an optimal learning experience. Moreover, the continuous learning capabilities of the system allow it to predict the most effective path for each user, adjusting the difficulty in real-time based on responses, feedback, and predictive models.

The Dynamic Question Generation Engine is at the heart of the system, generating questions based on a detailed understanding of the user's skill profile and domain-specific knowledge. By using template-based generation and sequence-to-sequence models, the system is able to create novel, diverse, and highly personalized questions. The use of ontology-based generation ensures that questions are domain-relevant and up-to-date, allowing the system to adapt to a wide variety of subjects and disciplines.

Furthermore, the Real-Time Feedback System plays an essential role in ensuring that the user remains engaged throughout the assessment. The feedback is not only limited to correctness but also includes personalized insights into areas that need improvement, thereby guiding the user's learning journey. As users progress, the system continually adjusts to their performance, providing a smooth and adaptive learning curve that maximizes knowledge retention and skill development.

This AI-based model has vast potential across various domains, such as education, corporate training, and professional certification exams. It offers personalized, scalable, and adaptive assessment solutions that cater to individual learning styles and proficiency levels. The model's integration of cutting-edge AI techniques guarantees that users receive a fair, accurate, and challenging evaluation of their skills, promoting continuous growth and improvement.

In conclusion, the proposed system represents a significant step forward in AI-driven education and skill assessment. By combining NLP, ML, and DL techniques, the system offers a highly adaptive, personalized, and efficient approach to assessing and enhancing user skills. As the system evolves with more data and user interactions, its ability to provide highly relevant and dynamic assessments will only improve, contributing to the future of personalized learning and skill evaluation. Through this innovative approach, the system paves the way for more effective, individualized learning experiences that align with the evolving needs of modern education and training landscapes.

This conclusion summarizes all the core components and features of the AI-based skill assessment model, reflecting the detailed points discussed in previous sections. It emphasizes the technical advancements of the system and its potential applications across various fields.