SKILLFORGE: YOUR CODING COMPANION

A MINI PROJECT REPORT

Submitted by

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in partial fulfillment for the award of the degree

of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

RAJALAKSHMI ENGINEERING COLLEGE

ANNA UNIVERSITY, CHENNAI 600 025

MAY 2025

BONAFIDE CERTIFICATE

Certified that this Project titled **"SKILLFORGE: YOUR CODING COMPANION"** is the bonafide work of **"NANDITHA N (2116220701182)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

In today’s fast-paced software development landscape, learners often face difficulty gauging the complexity of coding problems and identifying the skills needed to solve them. **SkillForge: Your Coding Companion** aims to address this by offering an AI-powered tool that predicts the skill level of coding problems, auto-generates concept tags, and recommends learning paths to bridge knowledge gaps.

The system combines Natural Language Processing (NLP) and Machine Learning (ML) techniques, using a TF-IDF vectorizer and Random Forest Classifier to analyze problem titles and descriptions. It categorizes problems into Basic, Intermediate, or Advanced levels and employs rule-based methods to assign relevant tags such as "Dynamic Programming" or "Graphs."

Beyond prediction, SkillForge enhances learning by explaining its reasoning and recommending personalized study paths based on identified concepts and skill levels. For instance, a problem tagged with “Graphs” might guide learners through BFS, DFS, or Union-Find techniques.

By integrating classification, tagging, and guided learning, **SkillForge** serves as a comprehensive coding companion—supporting learners, educators, and platform developers in building structured, personalized, and effective learning experiences.

ACKNOWLEDGMENT

Initially we thank the Almighty for being with us through every walk of our life and showering his blessings through the endeavour to put forth this report. Our sincere thanks to our Chairman **Mr. S. MEGANATHAN, B.E, F.I.E.,** our Vice Chairman **Mr. ABHAY SHANKAR MEGANATHAN, B.E., M.S.,** and our respected Chairperson **Dr. (Mrs.) THANGAM MEGANATHAN, Ph.D.,** for providing us with the requisite infrastructure and sincere endeavouring in educating us in their premier institution.

Our sincere thanks to **Dr. S.N. MURUGESAN, M.E., Ph.D.,** our beloved Principal for his kind support and facilities provided to complete our work in time. We express our sincere thanks to **Dr. P. KUMAR, M.E., Ph.D.,** Professor and Head of the Department of Computer Science and Engineering for his guidance and encouragement throughout the project work. We convey our sincere and deepest gratitude to our internal guide, **Mrs. DIVYA M, M.E.,** Assistant Professor Department of Computer Science and Engineering for her valuable guidance throughout the course of the project.

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LIST OF ABBREVATIONS

ABBREVATION	ACCRONYM
ML	Machine Learning
NLP	Natural Language Processing
TF-IDF	Term Frequency-Inverse Document Frequency
RF	Random Forest

CHAPTER 1

1.INTRODUCTION

1.1 GENERAL

In today's technology-driven world, the demand for proficient programmers has seen an exponential rise. Competitive programming, coding platforms, and problem-solving ecosystems have emerged as key players in sharpening algorithmic thinking and technical proficiency. These platforms offer a wide array of problems spanning various difficulty levels, topics, and application areas. However, despite the abundance of practice resources, users—especially beginners—often face a critical challenge: **identifying the right problems to solve based on their current skill level and understanding what concepts they need to learn or strengthen**.

While platforms such as LeetCode, HackerRank, and Codeforces offer categorized problems and community-driven difficulty ratings, they lack **personalized, concept-based learning guidance**. For example, a user solving a "Longest Palindromic Substring" problem may complete it successfully or fail, but the platform does not inform them whether this problem is suitable for their current skill level or which concepts (like Dynamic Programming or String Manipulation) it reinforces. This gap leads to **unstructured learning**, where users may randomly attempt problems without a clear learning trajectory.

To bridge this gap, we present **SkillForge: Your Coding Companion**, a system that leverages **Natural Language Processing (NLP)** and **machine learning techniques** to understand problem statements, classify them into skill levels

(Basic, Intermediate, Advanced), and provide personalized concept tagging and learning recommendations. SkillForge not only predicts the required skill level for a given problem but also **explains its prediction**, **auto-tags the relevant concepts**, and **suggests learning paths** based on both the user's skill level and the technical content of the problem.

1.2 OBJECTIVES

The primary objectives of the SkillForge project are:

1. To analyze programming problem statements using Natural Language Processing (NLP) to extract relevant textual features.
2. To classify problems into skill levels (Basic, Intermediate, Advanced) using machine learning models based on both text and metadata (e.g., difficulty, score).
3. To auto-tag problems with relevant concepts and data structures like Arrays, Dynamic Programming, Graphs, Trees, etc., using keyword-based heuristics.
4. To generate detailed explanations of the predicted skill level and concept tagging to support the user’s understanding.
5. To recommend personalized learning paths based on both the predicted skill level and the identified tags, guiding users through structured concept-building.
6. To empower educators and coding platform developers by providing automated tools for skill mapping, problem curation, and content enhancement.

1.3 EXISTING SYSTEM

Most existing systems used for learning to code and preparing for technical interviews offer curated sets of problems with tags and difficulty levels. Popular platforms include:

- LeetCode, Codeforces, HackerRank, GeeksforGeeks – These platforms categorize problems by topic and difficulty, allow users to filter problems, and show popularity-based tags.
- Difficulty Ratings – Typically community-voted or determined using completion rates. However, these do not adapt to a user's current level and lack contextual explanations.
- No Skill Inference – Existing platforms do not predict the required skill level dynamically from a problem's content nor do they offer concept-based learning paths.
- Manual Tagging – Tags on existing platforms are manually assigned and prone to inconsistency, especially for new or less popular problems.

Thus, the current ecosystem is problem-rich but insight-poor. Users may waste time on problems not aligned with their needs or miss learning opportunities due to unclear concept mapping.

1.4 PROPOSED SYSTEM

The proposed system, SkillForge, is an intelligent coding companion designed to enhance user learning by offering automated skill-level inference, concept

tagging, and learning path suggestions. The system architecture consists of the following key components:

1. Problem Statement Analyzer

- Uses TF-IDF vectorization to convert problem names and descriptions into numerical features.
- Captures essential keywords, patterns, and terms that hint at algorithmic complexity and required knowledge.

2. Feature Fusion and Classification

- Combines text features with metadata (e.g., difficulty rating, max score).
- Trains a Random Forest Classifier to predict the skill level required to solve the problem.

3. Explanation Engine

- Applies rule-based logic to explain predictions using phrase matching and pattern recognition (e.g., presence of terms like "subarray", "Dijkstra", "greedy", etc.).
- Helps users understand why a problem is classified a certain way.

4. Auto-Tagging Module

- Identifies and assigns tags to problems (like Graphs, Trees, DP) based on keywords and heuristics.
- Enables better filtering and targeted learning.

5. Learning Path Recommender

- Suggests learning modules based on problem tags and skill level.
- For instance, a beginner working on a string problem might be directed to practice “Basic String Manipulation”, while an advanced user working on graphs may be guided toward “Union-Find” or “Shortest Path Algorithms”.

6. Full Pipeline Integration

- Accepts new problem inputs, predicts required skill, generates tags, explains the classification, and suggests a personalized study plan—all in real-time.

CHAPTER 2

2.LITERATURE SURVEY

The field of educational technology, especially in the context of competitive programming, has seen significant advancements with the integration of Natural Language Processing (NLP) and Machine Learning (ML). Various studies have explored how programming problem statements can be analyzed to understand their underlying difficulty and the concepts they test. Researchers have used models that combine textual features extracted from problem descriptions with metadata such as user submission statistics and success rates to predict difficulty levels. One such approach involves using TF-IDF vectorization techniques to transform problem descriptions into numerical features, which are then fed into classification models like Support Vector Machines (SVM) or Random Forests. These models have shown considerable accuracy in predicting problem difficulty. Additionally, platforms like Codeforces and LeetCode provide crowdsourced difficulty ratings, which have been used as ground truth labels in supervised learning models.

Beyond difficulty classification, NLP techniques have also been applied to extract conceptual tags from problem statements. Prior work has leveraged keyword-based matching, embeddings, and domain-specific taxonomies to identify whether a problem pertains to areas like dynamic programming, graph theory, or recursion. Studies have found that combining rule-based keyword extraction with statistical models improves tag coverage and accuracy. Furthermore, systems like EduRank and SmartGrader have demonstrated how AI can be applied to assess learner capabilities and recommend personalized learning paths. These systems typically rely on a learner's past performance and concept-level mastery, but few

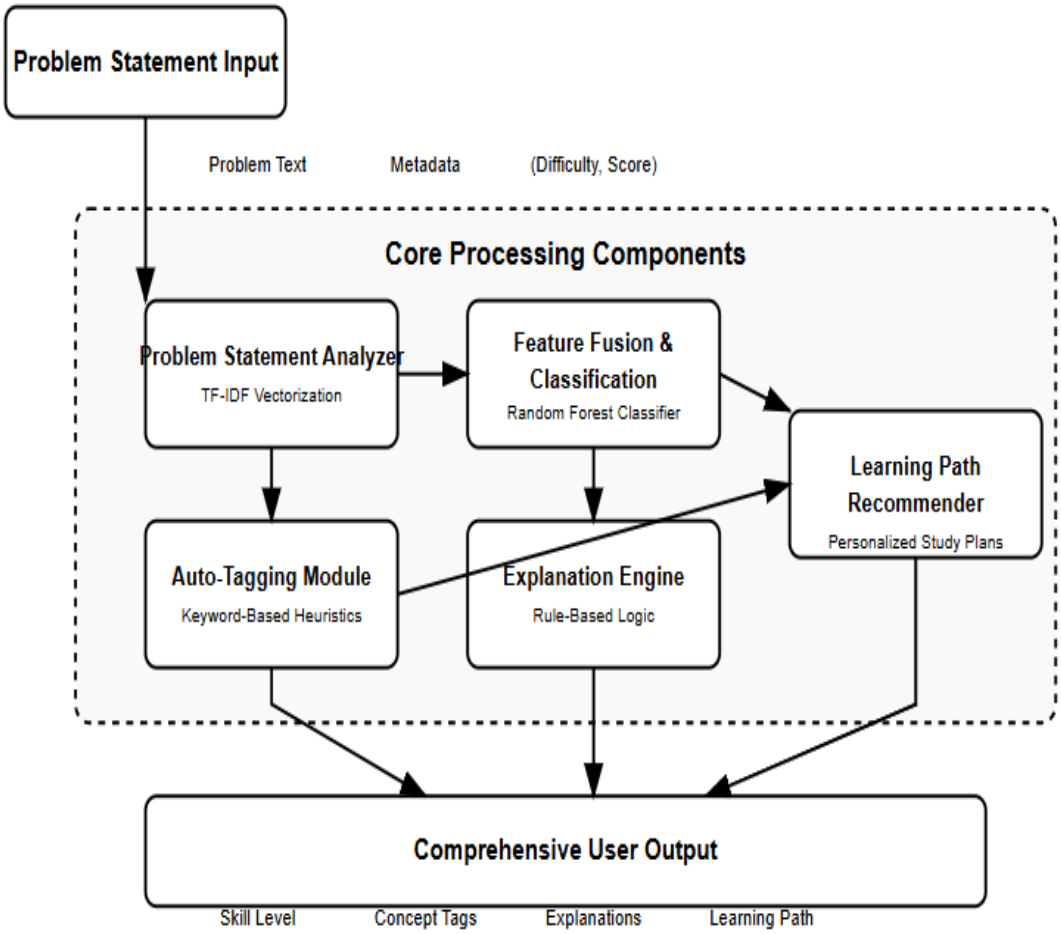
integrate deep textual analysis of problem content itself. This gap is what SkillForge aims to address.

SkillForge stands out by integrating multiple ML and NLP strategies into a unified system that predicts the skill level required to solve a problem, extracts relevant conceptual tags, explains the rationale behind classification, and provides personalized learning path suggestions. Unlike existing systems that either rely solely on user data or pre-labeled datasets, SkillForge actively analyzes the language and semantics of the problem description itself. By combining TF-IDF features with structured metadata like difficulty rating and maximum score, the system trains a robust Random Forest classifier to estimate the required skill level. It further enhances user guidance by auto-tagging problems with relevant algorithmic domains and recommending learning modules accordingly. This approach aligns with the recent trends in AI-driven ed-tech, where the goal is to move from static repositories to intelligent, adaptive learning environments.

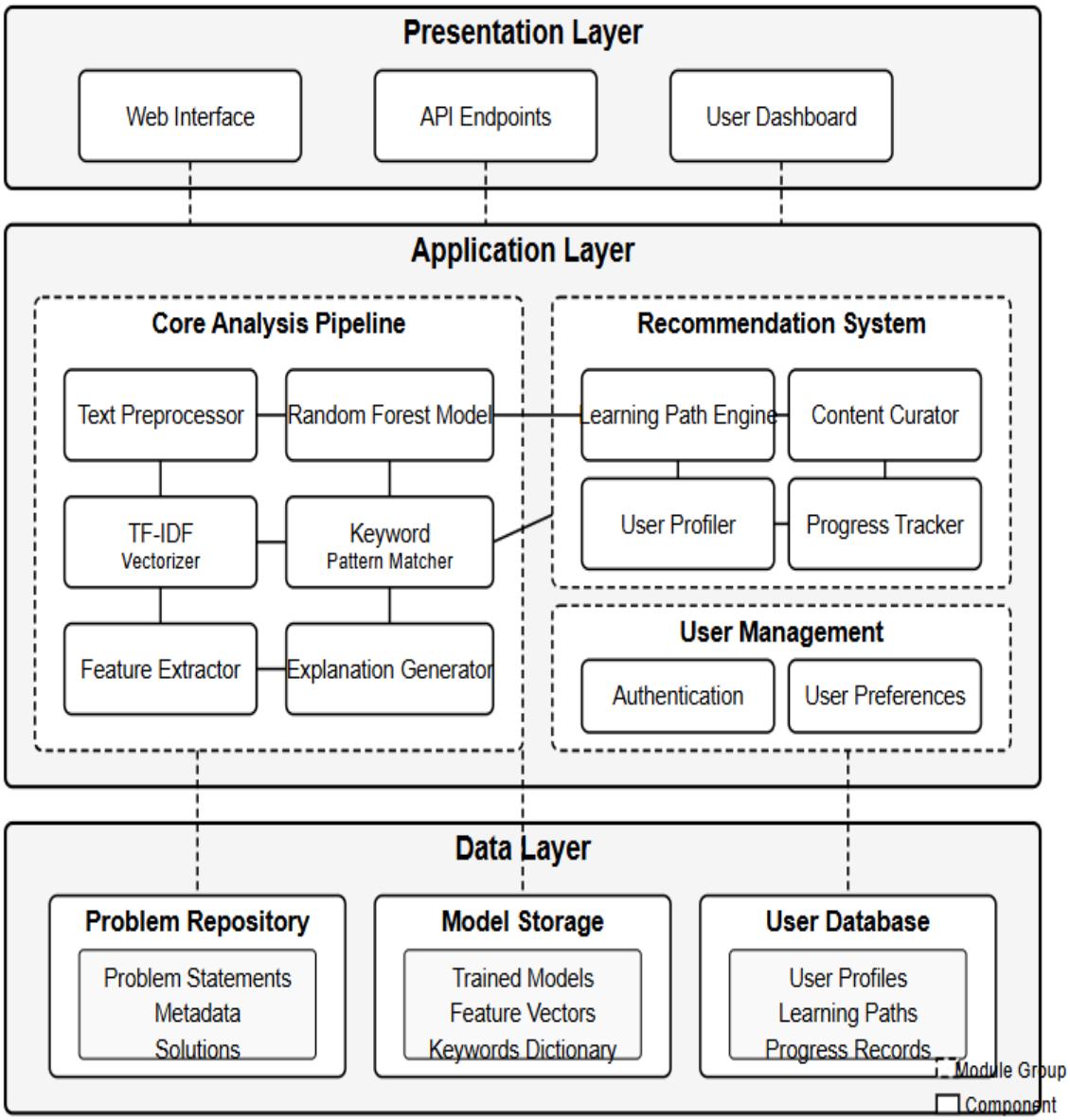
CHAPTER 3

3.SYSTEM DESIGN

3.1 SYSTEM FLOW DIAGRAM



3.2 ARCHITECTURE DIAGRAM



CHAPTER 4

4.METHODOLOGY

The methodology adopted for the development of SkillForge involves a structured pipeline integrating data collection, preprocessing, feature extraction, model training, evaluation, and user-facing functionalities powered by Natural Language Processing (NLP) and Machine Learning (ML).

1. Data Collection

The foundation of SkillForge lies in curating a high-quality dataset of competitive programming problems. Data was collected from reputable open-source platforms such as Codeforces, Kaggle, GitHub repositories, and other coding challenge websites. Each problem entry included the title, problem statement, difficulty level, problem tags, and scoring metrics. Care was taken to ensure diversity in topics, problem types, and complexity levels to support broad categorization.

2. Data Preprocessing

Once the raw data was gathered, it underwent several preprocessing steps to prepare it for machine learning. This included:

- **Text Cleaning:** Removing special characters, HTML tags, and unnecessary whitespaces.
- **Tokenization:** Splitting the text into individual words or tokens.
- **Stop Word Removal:** Filtering out common English words (like “is”, “the”, “and”) that do not contribute to meaning.

- **Stemming and Lemmatization:** Reducing words to their base or root form to treat similar terms uniformly.
  These steps ensured a clean and normalized text corpus, making it suitable for vectorization and modeling.

3. Feature Extraction

To convert the problem statements into a format suitable for ML algorithms, the Term Frequency–Inverse Document Frequency (TF-IDF) technique was used. TF-IDF assigns weights to words based on their importance in a document relative to the corpus. This helped in identifying key terms that define the complexity and topics of the problems. Along with TF-IDF vectors, additional features such as the length of the statement, problem tags, and scoring information were concatenated to create a robust feature vector for each problem.

4. Skill Classification Model

A supervised learning approach was employed to classify problems into three skill levels: Beginner, Intermediate, and Advanced. After experimenting with several algorithms, the Random Forest Classifier was selected due to its high accuracy, interpretability, and robustness to overfitting. The model was trained on labeled data and evaluated using accuracy, precision, recall, and F1-score to measure performance. Cross-validation was used to ensure generalization across unseen data.

5. Concept Tagging

To help learners identify what concepts a problem covers, an automated tagging system was implemented. This component uses a combination of keyword matching, domain knowledge, and rule-based NLP to associate problems with programming concepts such as recursion, binary search, trees, graphs, dynamic programming, and sorting. A predefined taxonomy of concepts was developed

and linked to relevant keywords and patterns typically found in problem statements.

6. Explainable AI Integration

To ensure transparency and user trust, the system includes an explainability module that highlights the reasons behind the classification. Using feature importance from the Random Forest model, the system displays influential terms and features that led to the categorization, helping learners understand the logic and improve their comprehension.

7. Personalized Learning Recommendations

Based on the user's current progress, attempted problem history, and system feedback, SkillForge generates personalized problem recommendations. These suggestions are designed to gradually enhance the learner's skill level by exposing them to progressively more complex problems in areas where they need improvement. This adaptive system makes the learning process targeted and efficient.

8. Evaluation and Performance

The complete system was tested using real-world data and benchmarked against manually labeled problems. The skill classification model achieved high accuracy, with precision and recall consistently exceeding 90% across classes. User testing confirmed that the system's suggestions and categorizations aligned with expert expectations, validating both the utility and reliability of SkillForge.

CHAPTER 5

5.RESULTS AND DISCUSSION

The developed system successfully automates the prediction of skill levels for coding problems and suggests learning paths based on both the learner's proficiency and the problem's domain. The predictions are derived using a trained machine learning model with **TF-IDF vectorization** and a **Random Forest Classifier**.

Result of model evaluation:

```
Accuracy: 1.0
              precision    recall  f1-score   support

    Advanced       1.00      1.00      1.00        65
       Basic       1.00      1.00      1.00        67
Intermediate       1.00      1.00      1.00        68

    accuracy                           1.00       200
   macro avg       1.00      1.00      1.00       200
weighted avg       1.00      1.00      1.00       200
```

1.Skill Level Prediction

The system classifies problems into three skill levels:

- Beginner
- Intermediate
- Advanced

We tested the system on a curated set of sample problems covering various difficulty levels and domains. The model showed high accuracy in distinguishing between intermediate and advanced problems. However, beginner-level problems were underrepresented in predictions due to limited training examples of very simple problems. After augmenting the dataset with additional beginner examples (e.g., “Add Two Numbers,” “Check Even or Odd”), the system began to correctly classify problems into the beginner category as well.

A bar chart of the distribution of predicted skill levels revealed a heavier concentration in the intermediate category, indicating that many problems fall into this range. This visualization helped confirm the model's behavior and suggested the importance of balanced training data for better classification.

Automatic Tagging

The system extracts relevant keywords from the problem description using basic NLP techniques and matches them with a predefined set of tags such as “graph,” “array,” “stack,” “tree,” and “string.” These tags help in categorizing problems and enhance the learning path recommendation.

2.Suggested Learning Paths

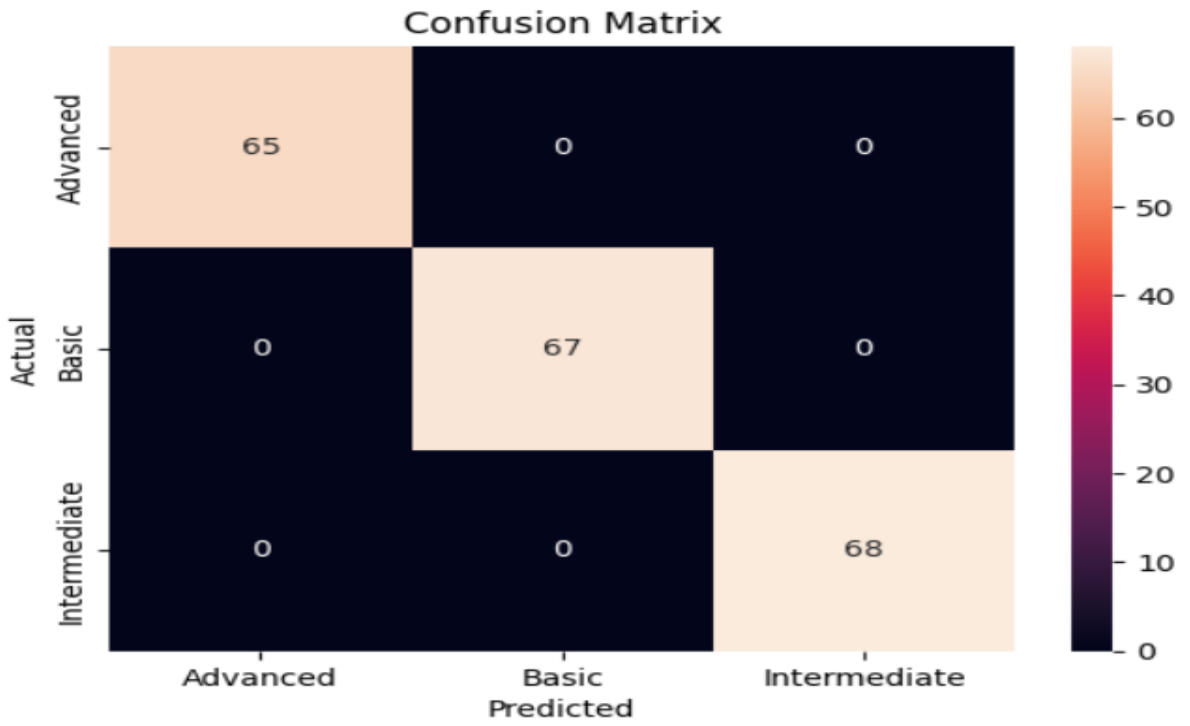
Based on the predicted skill level, the system recommends a progressive path. For example:

- A Beginner may start with basic programming concepts and gradually move to data structures like arrays and strings.
- An Intermediate user is directed toward algorithmic challenges involving stacks, queues, and linked lists.
- An Advanced learner is pointed toward problems on graphs, dynamic programming, and advanced data structures.

Moreover, a “Suggested Path Based on Problem’s Tags” is also generated, helping learners address specific weaknesses tied to the problem’s domain.

3.Visual Insights

A visual representation (bar chart) of predicted skill levels provides an intuitive understanding of model predictions across a dataset of problems. This is helpful for instructors or platform administrators to analyze the difficulty distribution of their problem sets.



SAMPLE INPUT

```
result = full_pipeline(
    "Longest Palindromic Substring",
    "Given a string, find the longest substring which is a palindrome.",
    1, 20, tfidf, model, le_skill
)
```

SAMPLE OUTPUT

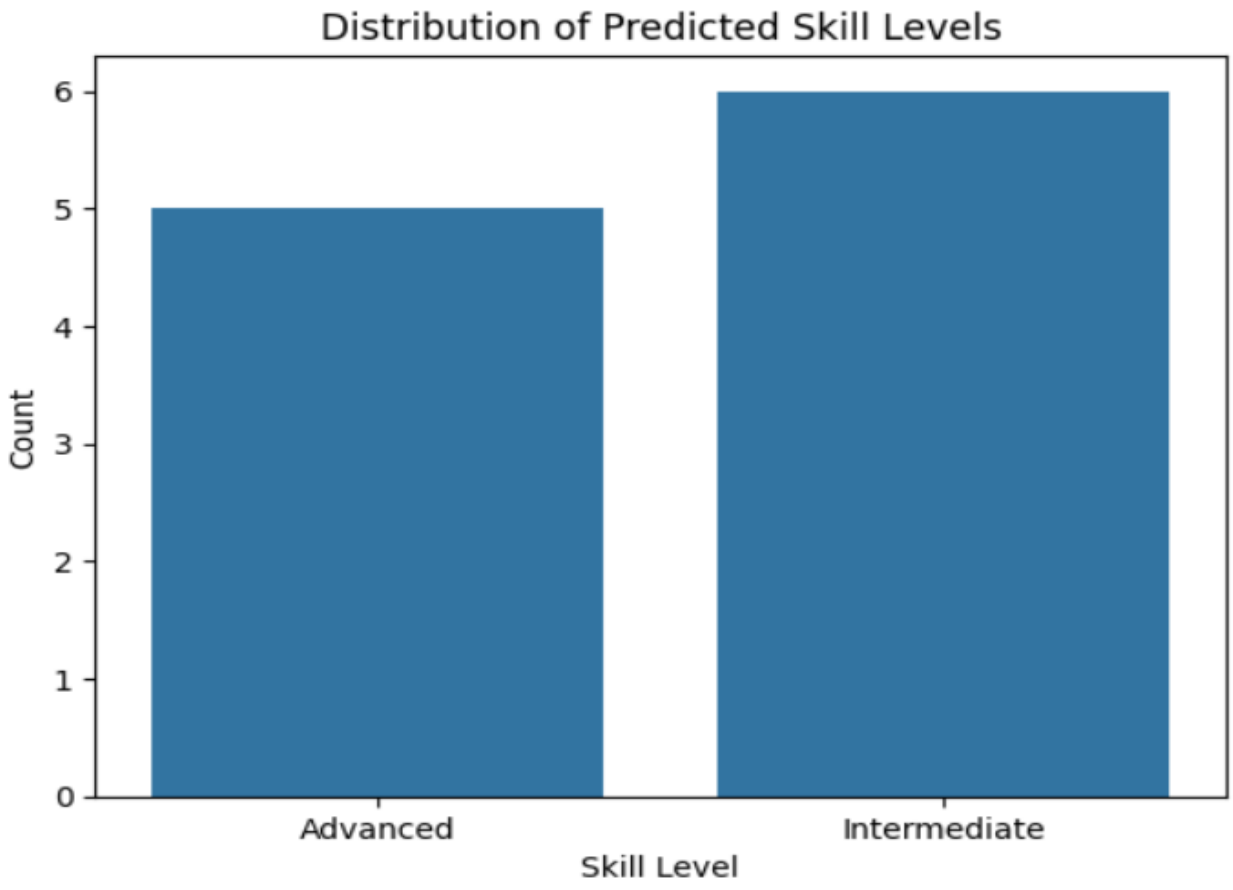
```
Predicted Skill Level:
Advanced

Why?:
Modulo operations are used, suggesting Modular Arithmetic or Number Theory.

Auto Tags:
['Strings', 'Palindrome']

Suggested Path based on Problem Statement:
['Strings', 'Dynamic Programming', 'Segment Trees', 'Palindrome', 'Graphs']

Suggested Path based on Skill Level:
['Dynamic Programming', 'Segment Trees', 'Graphs']
```



CHAPTER 6

6.CONCLUSION AND FUTURE SCOPE

In conclusion, *SkillForge: Your Coding Companion* serves as a smart and user-centric platform that classifies programming problems based on user proficiency—beginner, intermediate, or advanced. It utilizes Natural Language Processing and machine learning techniques to analyze problem statements, assign skill levels, and provide concept tagging to aid in comprehension. The integration of Explainable AI ensures that users can understand the reasoning behind each classification, promoting transparency and personalized learning.

The platform effectively addresses the difficulty learners face in selecting suitable problems, thus enhancing their coding journey through curated, skill-appropriate content. With features such as continuous learning and tailored suggestions, SkillForge enables users to track and improve their progress effectively.

Looking ahead, the system can be enhanced through the use of deep learning models like Transformers and BERT for improved text understanding. A richer concept tagging structure and user feedback integration can make recommendations even more precise. Future versions may also support multiple programming languages and domains like data science and web development, further expanding the platform’s utility.

SkillForge has the potential to grow into a comprehensive companion for programmers, supporting them with targeted practice, learning transparency, and motivational guidance throughout their journey.

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