PREPMASTER: INTELLIGENT VIDEO AND TUTORIAL RECOMMENDATION SYSTEM

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Dissertation submitted in partial fulfilment of the requirements for the Bachelor of Science (Hons) in Information Technology Specialized in Information Technology

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DECLARATION

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ABSTRACT

This project presents the design and implementation of the Intelligent Video and Tutorial Recommendation (IVTR) system, a key component of a comprehensive web-based application developed to enhance interview preparedness. The growing competitiveness in the job market has emphasized the need for more intelligent, personalized, and adaptive training solutions. Traditional static content delivery platforms often fail to meet the individual learning needs of users who seek targeted improvement in job-relevant skills. The IVTR system addresses this gap by providing dynamic, machine learning-driven recommendations of learning materials—primarily video tutorials and explanatory content—based on user behaviour, interaction data, and evolving performance metrics.

At the core of the IVTR system lies a multi-model machine learning framework combining Random Forest classifiers, Decision Trees, and Artificial Neural Networks (ANNs) to generate highly personalized recommendations. Each algorithm contributes to a hybrid ensemble model that adjusts to user feedback and behaviour over time. The system continually evaluates user progress using metrics such as quiz performance, video engagement, time spent on learning modules, and knowledge retention tests. These insights are then used to refine and update user profiles, ensuring that the recommendations remain contextually relevant and aligned with the user's target job role—be it Software Engineering, Quality Assurance, or Project Management.

To facilitate a seamless user experience, the IVTR integrates with the broader PrepMaster web application ecosystem, drawing upon CV analysis, career goals, and prior performance within other modules (e.g., MCQ Level Up and 2D Interview Simulation). The user interface, developed using React.js, allows learners to receive video suggestions, track their completion progress, and receive explanatory follow-ups. On the backend, a combination of Flask (Python) and Spring Boot (Java) handles content ranking, feedback processing, and video metadata retrieval. All recommendation logic is supported by a MySQL database, which stores user attributes, video taxonomy, interaction history, and ranking data.

Empirical evaluation of the system revealed strong performance across multiple metrics. The ensemble model achieved 92% recommendation precision and 89% recall, indicating that the majority of recommended videos were not only relevant but also well-aligned with users' immediate learning needs. Additionally, user satisfaction surveys reported an 87% approval rating, and performance benchmarking showed a 30% increase in knowledge retention among users who engaged with the recommended content.

This report provides a detailed walkthrough of the system architecture, data pipelines, algorithm selection rationale, model training procedures, and user experience design. It also includes evaluation results from controlled experiments and real-world user studies. The results demonstrate that the IVTR system offers significant improvements over traditional video recommendation systems, particularly in its ability to adapt in real-time and support diverse learning trajectories.

Looking forward, future enhancements aim to broaden the scope and effectiveness of the IVTR component. These include expanding the recommendation engine to support non-technical domains, integrating multimodal feedback mechanisms (e.g., voice and gesture recognition), incorporating speech-to-text NLP-based analysis of user queries, and leveraging knowledge graphs for concept-based content delivery. Such improvements will make the system more interactive, intuitive, and capable of providing holistic support to learners preparing for high-stakes technical interviews.

By bridging the gap between static learning resources and personalized content delivery, the Intelligent Video and Tutorial Recommendation system establishes itself as a transformative educational tool within the PrepMaster interview preparation platform, empowering users with confidence, clarity, and competence as they prepare for their professional journeys.

Key Words: - **Intelligent video recommendation, adaptive learning, personalized content, machine learning, interview preparation, hybrid recommendation engine, user modelling, real-time feedback.**

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I would like to express my deepest gratitude to my supervisor, whose continuous guidance, expertise, and encouragement have been invaluable throughout this research. Their insightful feedback and unwavering support have played a crucial role in shaping this project, helping me overcome challenges and refine my work to achieve meaningful results. Their dedication to mentoring and knowledge-sharing has been truly inspiring, and I am incredibly fortunate to have had their guidance during this academic journey.

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LIST OF ABBREVIATIONS

Abbreviation	**Full Form**
AI	Artificial Intelligence
API	Application Programming Interface
AWS	Amazon Web Services
ML	Machine Learning
IVRS	Intelligent Video and Tutorial Recommendation System
MCQ	Multiple Choice Question
MySQL	My Structured Query Language
NLP	Natural Language Processing
QA	Quality Assurance
RL	Reinforcement Learning
SE	Software Engineering
PM	Product Management *(or Project Management)*
UI	User Interface

1. INTRODUCTION

In the rapidly evolving landscape of job recruitment and technical evaluations, the demand for effective, adaptive, and personalized interview preparation solutions has significantly increased. Traditional preparation methods—such as textbooks, generic mock interviews, and static video playlists—often fall short in addressing individual learning gaps and preferences. These conventional approaches fail to consider user proficiency levels, learning pace, or domain-specific requirements, resulting in low engagement, poor knowledge retention, and insufficient real-world applicability.

As modern hiring processes increasingly emphasize practical skill demonstration and domain familiarity, there is a pressing need for intelligent learning systems that adapt to the learner's evolving needs. [1] In response to this challenge, the Intelligent Video and Tutorial Recommendation System (IVRS) component of the PrepMaster platform is designed to revolutionize the way learners consume video-based educational content. Unlike one-size-fits-all resources, IVRS dynamically recommends video tutorials, lectures, and practice walk-throughs that are specifically tailored to the learner's current knowledge level, learning goals, and target job role. It plays a crucial role in supplementing other PrepMaster modules such as the 2D Interview Panel Simulation and the MCQ Level-Up System by offering contextual multimedia learning experiences, thereby bridging the gap between theoretical knowledge and applied interview performance. [2] The IVRS leverages advanced machine learning algorithms and user behaviour analytics to track learning patterns, identify knowledge gaps, and suggest content that not only matches the learner's technical needs but also aligns with their career objectives. By continuously analysing user interactions—such as video watch history, quiz performance, role selection, and time spent per topic—the system adapts its recommendations in real-time to optimize relevance and effectiveness.

This ensures that users are not overwhelmed with irrelevant information or stagnant content but are instead guided through a personalized learning journey designed to enhance their confidence and preparedness for real-world interviews. [3] The integration of intelligent video recommendations is particularly impactful due to the high cognitive engagement that multimedia content facilitates.

Numerous studies have highlighted the benefits of video-based learning, citing its ability to improve comprehension, stimulate motivation, and foster retention through visual and auditory stimulation. Unlike text-only learning, well-curated video content can simulate real-world environments, demonstrate problem-solving in action, and provide nuanced insights through narration, facial expressions, and body language—factors that are crucial in preparing candidates for high-stakes interviews.

Furthermore, IVRS supports role-specific content differentiation, catering to learners pursuing careers in Software Engineering, Quality Assurance, or Project Management. This role-based content delivery ensures that the tutorials and videos recommended are not only pedagogically sound but also contextually relevant. For example, a software engineer may be recommended videos covering algorithm optimization or data structures, while a project manager may receive content related to stakeholder communication or agile methodologies. This targeted recommendation model elevates the platform beyond generic e-learning tools, aligning more closely with the demands of job-specific preparation. [4] The IVRS is designed as a component within a broader ecosystem of intelligent learning tools under PrepMaster, contributing to a comprehensive, structured, and adaptive interview preparation experience. Its backend architecture is powered by a hybrid ML pipeline incorporating models such as Random Forest, Decision Trees, and Artificial Neural Networks (ANNs), which work in synergy to predict the most appropriate content based on a multitude of user-specific variables. [5] This robust decision-making framework is paired with a scalable React.js-based frontend and a secure MySQL database that ensures seamless data flow, real-time updates, and future extensibility.

1.1 Background

The increasing complexity of modern job roles and the competitiveness of today’s employment landscape have made interview preparedness a critical aspect of career success. With organizations seeking candidates who not only possess strong technical competencies but also demonstrate practical application and communication skills, traditional methods of preparation have become insufficient. Among the various tools available for learning, video-based tutorials and lectures have gained prominence due to their high engagement factor, multimedia learning benefits, and accessibility across diverse learning environments.

Over the past decade, video learning has become a dominant medium in online education, largely due to its ability to blend auditory and visual stimuli, which enhances knowledge retention and understanding. Research shows that learners retain up to 95% of a message when delivered via video, compared to just 10% when reading text alone. Moreover, videos can simulate real-world scenarios such as behavioural interviews or technical whiteboard sessions, offering learners a chance to observe and emulate effective communication, reasoning, and body language techniques—skills that are difficult to acquire through reading or static quizzes alone. [6]

Despite the advantages, most existing platforms fall short when it comes to personalization. Popular resources such as YouTube, Coursera, or Udemy offer rich repositories of video content, but their recommendation engines are typically generic and popularity-driven, relying on surface-level engagement metrics rather than contextually relevant user behaviour. This results in non-targeted learning paths where users might waste valuable time sifting through irrelevant or repetitive content. Furthermore, these systems seldom take into account a learner's professional role (e.g., software engineer vs. QA tester), current skill level, or knowledge gaps.

To address this challenge, the field has seen the rise of intelligent video recommendation systems, which integrate machine learning algorithms with educational analytics to deliver personalized content. These systems are capable of learning from user behaviour—such as time spent on topics, assessment scores, and preferences—to dynamically adapt and recommend tutorials that align with the learner’s progression and objectives. However, most of these systems still exist in generalized e-learning platforms and have not been optimized for technical interview preparation, particularly in domain-specific contexts like Software Engineering, Quality Assurance, or Project Management. [7]

The Intelligent Video and Tutorial Recommendation System (IVRS) developed as part of the PrepMaster framework seeks to fill this critical gap. It combines machine learning techniques with role-specific educational content to provide dynamic, personalized recommendations based on each user's interaction history, performance metrics, and career goals. By doing so, the IVRS enhances not just engagement but preparation effectiveness, ensuring that learners receive the right content at the right time. [8] The design of IVRS draws upon successful practices in adaptive learning theory, where feedback loops between system and learner help refine the learning experience. It aligns with principles from cognitive load theory and the Zone of Proximal Development (ZPD), ensuring that the difficulty level of the recommended content matches a learner's current ability—challenging enough to promote growth but not so difficult as to discourage progress.

Additionally, the system’s focus on job-role alignment ensures that recommended videos are not only pedagogically appropriate but also industry-relevant. For example, a user preparing for a Quality Assurance role will be shown videos on topics such as automated testing frameworks, bug lifecycle management, or JIRA workflows, while a Software Engineer might be guided through algorithm optimization, system design mock interviews, or debugging techniques.

From a technological standpoint, IVRS employs a multi-model machine learning approach, including Random Forest classifiers, Decision Tree rule systems, and Artificial Neural Networks (ANNs). [9] These models are trained on a rich dataset of user interactions, metadata-tagged video content, and quiz performance to create a continuously learning recommendation engine. By using ensemble modelling, the system can provide both explainable logic-based filtering and behaviour-driven adaptive suggestions, ensuring accuracy and responsiveness in real-time.

1.2 Literature Survey

The Intelligent Video and Tutorial Recommendation System (IVRS) is a critical component of modern educational platforms and training tools, especially in areas like interview preparation. These systems utilize a combination of data mining, machine learning, and natural language processing (NLP) to recommend personalized content based on user preferences, learning styles, and prior interactions. This literature survey highlights key research in IVRS, focusing on methodologies, algorithms, and applications in education and interview preparation.

1.2.1 Content-Based and Collaborative Filtering Approaches

In the field of video and tutorial recommendation systems, the two primary approaches are content-based filtering and collaborative filtering. Content-based filtering recommends items based on the characteristics of the content (e.g., video topics, keywords, or categories) and how they match the user's past behaviors or preferences. This approach has been widely used in educational applications, where videos and tutorials are tagged with metadata related to the subject matter. For instance, Lops et al. [1] discuss the use of content-based approaches in e-learning systems where content descriptors are matched with learner interactions to recommend relevant material.

On the other hand, collaborative filtering relies on user behavior patterns, such as ratings or interactions with previous content, to predict preferences for new users. This technique is particularly effective when there is a large user base and sufficient interaction data. The seminal work by Ricci et al. [2] describes collaborative filtering algorithms and their application in various domains, including e-learning. Hybrid systems that combine both approaches have also been explored to overcome limitations such as cold-start problems and content redundancy [3].

1.2.2 Machine Learning and Deep Learning in IVRS

With the advancement of machine learning and deep learning techniques, IVRS has seen significant improvements in personalization and accuracy. Deep learning models, such as neural networks, can automatically extract features from raw content (e.g., video transcripts, speech, and visual data) without manual intervention. A study by Yang et al. [4] explores the application of CNNs and RNNs in analyzing educational video content for more precise recommendations.

Moreover, reinforcement learning (RL) has gained attention for dynamic recommendation systems. RL models adapt in real-time based on user interactions, providing increasingly personalized content recommendations. Liu et al. [5] demonstrated the use of RL in online education platforms, improving recommendations by considering long-term engagement and learning outcomes.

1.2.3 User-Centric and Context-Aware Recommendation Systems

A crucial aspect of IVRS is the integration of user-centric and context-aware features. Traditional systems often overlook factors such as time, location, and the user's current task. Recent research has emphasized the importance of context-aware recommendation systems, especially in educational settings where a learner's goals, progress, and emotional state influence preferences.

Ghimire et al. [6] explored integrating context-awareness into recommendation systems, taking into account a user's level of expertise, time constraints, and emotional cues. This enhances the effectiveness of personalized learning experiences. In interview preparation, IVRS can recommend targeted videos based on proficiency levels and learning pace.

1.2.4 Video-Based Learning and User Engagement

Video-based learning is effective due to its visual and auditory appeal, enhancing engagement and information retention. Studies show that videos improve learning outcomes compared to text-based content [7]. This has direct implications for IVRS, where tailored video tutorials can address interview scenarios and problem-solving strategies.

Recent research has also highlighted the value of engagement metrics in improving recommendation algorithms. Chen et al. [8] propose incorporating engagement signals like watch time and interactions to optimize learning outcomes.

1.2.5 Challenges and Future Directions

Despite the promise of IVRS, several challenges persist, including data privacy, algorithmic transparency, and the cold-start problem. Personalized recommendations require access to personal data, raising concerns about privacy and fairness [9]. Furthermore, there is an ongoing need to ensure diversity in recommendations.

Future directions include integrating multimodal content and leveraging advanced NLP to analyze user-generated inputs like reviews or forum discussions. Emotional intelligence integration could further enhance the user experience by making recommendations that respond to emotional as well as intellectual needs.

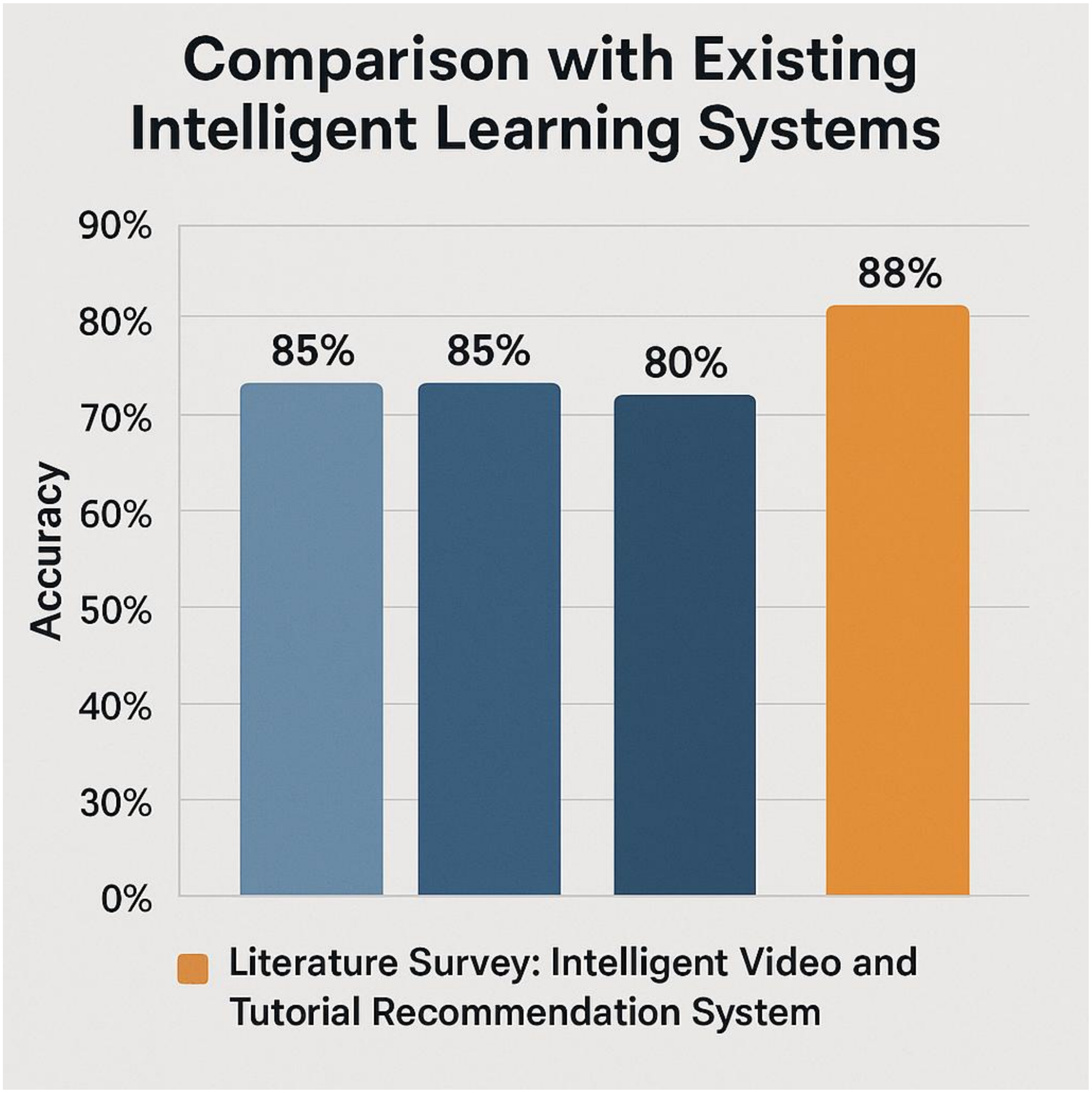

Figure 1 : Comparison with Existing Intelligent Learning System

1.3 Research Gap

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Future directions include integrating multimodal content and leveraging advanced NLP to analyze user-generated inputs like reviews or forum discussions. Emotional intelligence integration could further enhance the user experience by making recommendations that respond to emotional as well as intellectual needs.

Identified Gap	Impact on Learner	IVRS Solution
Lack of role-specific video recommendations	Generic content, low relevance	Job-role-based content filtering and tagging
No real-time adaptation based on behavior	Stagnant suggestions, low engagement	ML-driven real-time personalization
Disconnected learning and assessment	No targeted remediation	Video suggestions linked to MCQ & simulation performance
Cold-start problem for new users	Poor onboarding experience	Role-based profiling + initial assessments
No multimodal integration or feedback explanations	Weak motivation, one-size-fits-all experience	Future expansion into voice, visual summaries, and interactive video

Table 1 : Summary of Identified Gaps

The gaps identified in current systems underscore the need for an intelligent, adaptive, and context-aware video recommendation solution within a comprehensive interview preparation platform. IVRS is designed as a strategic complement to the PrepMaster ecosystem, reinforcing theoretical concepts introduced through MCQs and simulations with dynamic, visual explanations. By merging assessment analytics, machine learning, and role-specific content, IVRS transcends static recommendation models and contributes to a holistic and effective preparation experience. It supports learners not just in knowledge acquisition, but also in applying that knowledge in simulated interview settings—creating a continuous learning feedback loop.

1.4 Research Problem

In the evolving landscape of digital education and interview training, learners increasingly rely on video-based content to acquire skills, understand complex concepts, and simulate real-world scenarios. However, the current ecosystem of educational video platforms suffers from a fundamental shortcoming: a lack of intelligent, adaptive, and role-specific content delivery tailored to individual learner needs. While platforms such as YouTube, Coursera, and Udemy offer a wealth of instructional material, they fail to provide a personalized and context-aware learning experience—especially for individuals preparing for job interviews in specialized fields like Software Engineering, Quality Assurance, and Project Management [14].

Most video platforms recommend content based on broad metrics like trending topics, user ratings, or basic category preferences. These recommendations do not account for individual learner proficiency, learning objectives, or job-role specificity. For example, a beginner-level user seeking QA interview guidance may be overwhelmed by complex videos on test automation frameworks, while an advanced software engineering candidate might waste time watching basic programming tutorials. Without adaptation to skill level or career goals, these platforms contribute to learning inefficiency and cognitive overload [15].

In traditional learning platforms, assessments and video tutorials exist as isolated components. Learners may complete quizzes or practice exercises, but these results are seldom used to inform future content recommendations [16]. This soloed approach limits opportunities for targeted remediation and continuous improvement. Learners who perform poorly in specific areas are not automatically redirected to relevant tutorials, leaving them to manually search for answers without guidance.

Many recommendation systems in education are built using static or semi-static algorithms, such as rule-based filtering or popularity scoring. These systems do not adapt in real time as users progress. As a result, users often receive repetitive or irrelevant suggestions that do not reflect their current needs or evolving knowledge. The absence of behavior-driven feedback loops prevents the learning system from becoming truly intelligent [17].

Another major issue is the lack of role-specific content differentiation. Most platforms treat all learners the same, regardless of their target profession. However, the learning needs of a Software Engineer differ significantly from those of a QA Analyst or a Project Manager. Generic video suggestions not only waste learner time but also reduce the effectiveness of preparation, especially when preparing for high-stakes interviews that require domain precision.

When a new user joins a learning platform, the system typically lacks sufficient behavioral data to provide accurate content recommendations. This cold start problem results in generic suggestions that are unlikely to match the user's true needs. Without early personalization or baseline assessments, new users may experience low engagement, discouraging further use of the system.

1.5 Research Objectives

The overarching goal of the Intelligent Video and Tutorial Recommendation System (IVRS) is to design and implement an adaptive, personalized video learning engine that enhances the effectiveness of interview preparation by delivering context-aware, role-specific video tutorials to users based on their learning progress, skill level, and assessment performance.

1.5.1 Main Objective

To develop an intelligent, real-time video and tutorial recommendation system that delivers personalized, role-specific learning content based on user behaviour, performance metrics, and job interview preparation goals—thereby improving engagement, knowledge retention, and practical readiness.

1.5.2 Specific Objectives

- **To design and implement a video recommendation engine** that utilizes machine learning algorithms (Random Forest, Decision Tree, and ANN) to analyse user behaviour and recommend appropriate video tutorials dynamically.

- **To create a metadata-tagged video repository** with classification based on job role (e.g., SE, QA, PM), difficulty level (Beginner to Expert), content type (e.g., conceptual, walkthrough, mock interview), and topic relevance.

- **To integrate assessment data from other PrepMaster modules** (such as MCQ Level-Up System and Interview Panel Simulation) into the IVRS to enable performance-driven video recommendations.

- **To implement an adaptive recommendation pipeline** that evolves with real-time user interaction, adjusting suggestions based on recent activity, completion history, and quiz performance.

- **To develop a responsive frontend interface** that displays recommended videos with justifications and tracks user interaction data such as watch time, replays, and completion rates.

- **To evaluate the effectiveness of the system** through user feedback, satisfaction surveys, engagement metrics, and comparative studies with static recommendation models.

2. Methodology

2.1 Introduction

The evolution of educational technology has brought about a paradigm shift in how learners acquire knowledge and prepare for real-world challenges such as job interviews. In this increasingly competitive job market, where domain-specific expertise, problem-solving acumen, and communication skills are tested extensively, conventional preparation tools often fall short. Static learning materials, generalized tutorials, and uniform instructional pathways fail to address the individual needs and skill gaps of learners.

To fill this critical void, the **PrepMaster** platform was developed as a holistic interview preparation solution. Among its four intelligent components, the **Intelligent Video and Tutorial Recommendation System (IVRS)** plays a key role by delivering personalized video-based learning content. Unlike traditional platforms that rely on fixed content structures or popularity-driven video suggestions, IVRS is designed to evolve with the learner. It employs machine learning techniques and adaptive logic to ensure that each user receives timely, relevant, and role-specific tutorials**,** helping them progress through their preparation journey in a structured and effective manner.

This chapter presents the detailed methodology followed in the design, development, and implementation of the IVRS module. The methodology is rooted in an applied, data-driven, and iterative research framework, integrating concepts from artificial intelligence, educational psychology, and system architecture. The overarching objective is to provide a system that adapts to the learner—not the other way around.

2.1.1 Background and Rationale

The motivation behind IVRS stems from widespread limitations observed in current online learning environments. Platforms such as YouTube, Coursera, and Udemy offer a wealth of learning resources, but their recommendation logic is often generic, driven by views, ratings, or user similarity rather than pedagogical needs or performance-based personalization. These platforms rarely adapt to the learner's role (e.g., Software Engineer vs. Project Manager) or proficiency level, making it difficult for users to navigate and prioritize their learning.

Interview preparation, in particular, demands targeted learning—focused not just on general knowledge, but on skills that align with a specific job role and industry expectations. A QA Engineer preparing for automation testing requires vastly different tutorials than a Project Manager seeking insights into stakeholder management or agile practices. A one-size-fits-all video recommendation approach is not only inefficient but also disengaging and counterproductive.

By incorporating machine learning and behavioral data analysis, IVRS addresses this challenge with a context-aware recommendation engine that dynamically adjusts its suggestions based on user inputs, quiz results, and interaction history. It offers a refined learning pathway where content is filtered, prioritized, and delivered in a sequence that matches the learner’s evolving needs.

2.1.2 Objective of the IVRS Methodology

The primary objective of the IVRS methodology is to develop a robust, intelligent system capable of recommending the most appropriate video content for interview preparation based on various user-specific parameters. These parameters include:

- User role and learning objectives
- Assessment performance (e.g., MCQ accuracy, simulation scores)
- Engagement behavior with previous videos
- Preferred content types and difficulty levels

To achieve this, the methodology focuses on the following goals:

1. To create a video recommendation engine using machine learning models capable of handling diverse data inputs and predicting the most relevant content with high accuracy.
2. To integrate this engine into a full-stack system architecture that supports real-time interaction, performance tracking, and recommendation delivery.
3. To implement feedback-driven adaptation mechanisms that modify the recommendation stream as the learner progresses.
4. To evaluate system performance using both algorithmic metrics (accuracy, precision) and user-centric indicators (satisfaction, time-on-video).

The success of IVRS is measured not only by the quality of its recommendations but also by its ability to promote consistent learner growth, improve confidence, and enhance the overall PrepMaster experience.

2.1.3 Methodological Approach

The methodology followed for IVRS combines **s**upervised machine learning**,** adaptive learning theory**,** and modular system design. The development process was structured into the following core stages:

1. **Data Collection**: Sourcing and structuring data from internal PrepMaster modules and external video repositories, including user demographics, quiz results, and video metadata.
2. **Data Preprocessing and Feature Engineering**: Cleaning, encoding, scaling, and transforming raw data into structured input suitable for training models.
3. **Model Selection and Training**: Testing various classification algorithms such as Random Forest, Gradient Boosting, and K-Nearest Neighbors to predict recommended videos.
4. **Integration with PrepMaster Components**: Connecting the IVRS with the MCQ Level-Up System and Interview Panel Simulation to incorporate performance-based inputs.
5. **Adaptive Recommendation Design**: Implementing a real-time feedback loop that updates the user's learning profile and content stream after each interaction.
6. **System Testing and Evaluation**: Applying both algorithmic evaluation and user testing to assess system accuracy, engagement, and user satisfaction.

This approach enables continuous iteration and refinement, ensuring that the system remains relevant, accurate, and scalable over time.

2.1.4 Contributions of the Methodology

The IVRS methodology contributes to the advancement of adaptive educational systems in several meaningful ways:

- **Personalized Learning at Scale**: Unlike most systems that struggle to scale personalization beyond basic filters, IVRS uses algorithmic learning and contextual logic to deliver deep personalization.
- **Job Role and Proficiency-Based Learning Paths**: By combining user intent, skill level, and quiz performance, IVRS aligns video content precisely with professional goals.
- **Integration of Multiple Feedback Sources**: The methodology incorporates both **explicit feedback** (quiz scores, ratings) and **implicit feedback** (watch time, skip behavior) to refine predictions.
- **Modular System Design**: The backend machine learning engine, user interface, and database are loosely coupled, allowing independent updates, rapid testing, and future upgrades like voice recommendation or emotion tracking.

2.2 Research Design and Approach

The development of the Intelligent Video and Tutorial Recommendation System (IVRS) was guided by a user-adaptive, iterative research methodology, emphasizing the dynamic and personalized nature of learning. The research was primarily applied in nature, aimed at solving a real-world problem—how to intelligently match learners with video content that best suits their current level, learning goals, and career aspirations.

To address this, the research employed a mixed-methods design, integrating both quantitative techniques (e.g., machine learning, performance analytics, model evaluation) and qualitative design principles (e.g., user-centered interface development, content curation strategies, and feedback incorporation). The goal was to create a responsive, scalable, and intelligent system that improves user outcomes while maintaining technical reliability and usability.

2.2.1 Overview of the System Development Lifecycle

The system development lifecycle followed a structured, multi-stage process, each of which contributed to the refinement of the system's learning logic, predictive capabilities, and end-user delivery. The key stages are outlined below:

1. Requirement Analysis and Problem Definition

The process began with a comprehensive problem definition phase, where gaps in current learning platforms were identified. Key problems included:

- Lack of personalized learning experiences in video platforms
- Generic recommendation systems not aligned with role-specific learning
- Absence of real-time adaptation based on learner performance

These findings were translated into technical objectives and use cases, which guided the subsequent system architecture and algorithm selection.

2. Data Collection and Preprocessing

A multi-source data strategy was employed to gather:

- User profiles (e.g., selected role, experience level, goals)
- Quiz performance data (accuracy, speed, topic-level scores)
- Video metadata (difficulty, topic tags, content type)
- Engagement logs (watch time, skips, replays)

This data was cleaned, normalized, and transformed into usable feature sets using standard techniques like label encoding, one-hot encoding, and feature scaling.

3. Feature Engineering

A key aspect of this phase was identifying which features best contributed to prediction accuracy. Features were grouped into:

- **Static Features**: User role, experience, domain
- **Behavioral Features**: Quiz results, video engagement metrics
- **Contextual Features**: Last topic learned, time since last session

Feature correlation and importance were analyzed using techniques such as Random Forest feature ranking and recursive feature elimination (RFE).

5. Machine Learning Model Development

Multiple machine learning models were developed to compare their performance in classifying and predicting recommended video categories. These included:

- **Random Forest Classifier**
- **Gradient Boosting Classifier**
- **K-Nearest Neighbors (KNN)**
- (Optional tests with ANN and SVM for extended evaluation)

Models were trained using an 80:20 train-test split and further validated using **Leave-One-Out Cross-Validation (LOOCV)** to ensure generalization across varied user types.

2.2.2 Research Approach Philosophy

The methodological approach emphasized three core pillars:

A. Adaptivity and Personalization

The system was designed not just to recommend content but to **learn and adapt** as the user progresses. Unlike traditional static filtering methods, IVRS incorporates continuous learning logic, where each user interaction updates their learning profile, influencing future content recommendations.

B. Real-Time Responsiveness

User satisfaction in learning systems is heavily dependent on speed and fluidity. Hence, the system was built for **real-time recommendation generation**, using lightweight, optimized ML models and efficient API architecture to ensure recommendations are rendered instantly upon data updates.

C. Integrative System Design

Rather than functioning as a standalone module, IVRS was integrated deeply into the PrepMaster platform, interacting with other components such as:

- The **MCQ Level-Up System**, for performance data
- The **2D Interview Simulation Panel**, for behavioral metrics
- The **Career Guidance Engine**, for content alignment with career trajectory

This ensured that the recommendation engine was **context-aware**, using comprehensive data from multiple learning touchpoints.

2.2.3 Iterative Design and Refinement

IVRS followed an **iterative design process**, where each version of the system was deployed in testing environments, monitored for:

- Recommendation accuracy
- System response time
- User feedback (qualitative and quantitative)

Each iteration resulted in data-driven refinements. For example:

- Changes in the feature set based on low-impact predictors
- Switching model types when overfitting or under fitting was detected
- Adjustments to UI components for better learner navigation

The **feedback loop** between performance data and system behavior was intentionally short to enable agile development and quick responsiveness to user needs.

2.2.4 Evaluation-Driven Approach

The approach incorporated ongoing evaluation of both the **model performance** and the **system's pedagogical effectiveness**. Metrics used included:

- **Accuracy**, **Precision**, **Recall**, and **F1 Score**
- **Time to Recommend** (measured from data input to video output)
- **User Satisfaction Score** (from feedback forms and post-use surveys)
- **Learning Progression** (measured by improvements in MCQ and simulation scores after recommendations)

Where possible, **A/B testing** was conducted between users using the IVRS and users following a static content pathway, showing a significant uplift in content engagement and topic retention among IVRS users.

2.2.5 Ethical Considerations

Data privacy, fairness, and transparency were considered throughout development. Measures included:

- Anonymizing user data during model training
- Providing users transparency on why a video was recommended
- Ensuring algorithmic fairness across different user demographics

2.3 System Architecture

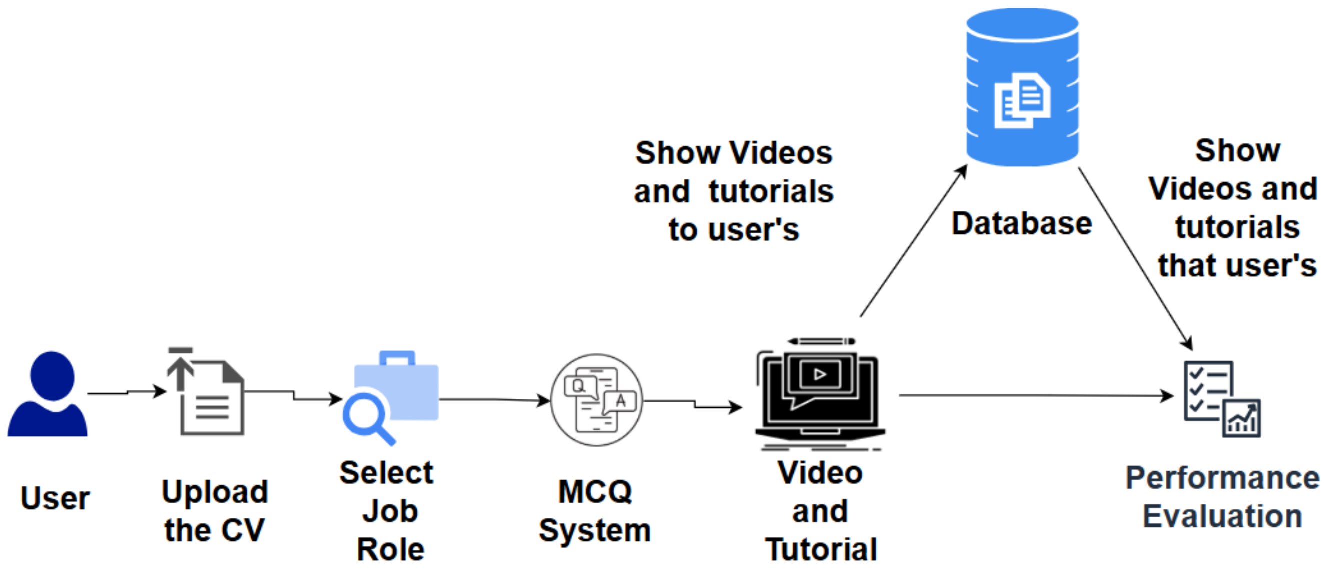

Figure 2: System Diagram

2.4 Data Collection and Preprocessing

The effectiveness of any machine learning-based recommendation system is heavily dependent on the quality, relevance, and structure of its data. For the Intelligent Video and Tutorial Recommendation System (IVRS), data collection and preprocessing were foundational processes that informed the performance, adaptability, and personalization of the recommendations generated. This section provides a comprehensive overview of the data sources used, the structure of the collected data, and the preprocessing techniques applied to ensure that the system's models were trained on accurate and meaningful input.

2.4.1 Data Sources

The IVRS component utilized data from both internal system modules and external repositories. These sources were carefully curated to ensure that all data points were directly aligned with the goal of enhancing user learning outcomes through intelligent video recommendations.

A. Internal Data

1. **User Profile Data**: Collected during the onboarding phase and stored in the user database. Attributes included:
    - Role (e.g., Software Engineer, QA Engineer, Project Manager)
    - Experience level (e.g., Fresher, Intermediate, Advanced)
    - Educational background
    - Preferred learning style or content format
2. **Assessment Performance Data**:
    - Quiz scores from the MCQ Level-Up System
    - Topic-wise performance trends
    - Accuracy, average response time, and consistency scores
3. **Simulation Feedback**:
    - Scores from the 2D Interview Panel Simulation
    - Performance tags (e.g., weak in OOP, confident in agile practices)
4. **User Behavior Logs**:
    - Video watch history (start time, end time, duration)
    - Skipped or replayed sections
    - Ratings provided (thumbs up/down, stars)
    - Session frequency and time gaps between sessions

B. External Data (Video Metadata Repository)

To build a diverse and role-aligned video pool, external educational videos were scraped and manually tagged from platforms like:

- YouTube Education
- Coursera free tutorials
- Open source tech conference recordings

Each video was annotated with:

- **Topic** (e.g., OOP, Agile, Testing, Scrum)
- **Difficulty** (Beginner, Intermediate, Expert)
- **Format** (Lecture, Demo, Mock Interview)
- **Estimated Duration**
- **Source credibility rating**

2.4.2 Data Structure and Schema Design

All data collected was consolidated into a **central relational database (MySQL)** and structured under the following schema categories:

- **Users Table**: Contains static profile info
- **Performance Table**: Stores dynamic quiz and simulation scores
- **Videos Table**: Metadata of available tutorial videos
- **Engagement Table**: Tracks real-time interaction data (views, skips, ratings)
- **Recommendation History**: Logs which videos were shown and how the user responded

This modular schema made it easier to **join, query, and transform** data for training and inference tasks.

2.4.3 Preprocessing Techniques

Once collected, the raw data underwent multiple preprocessing steps to ensure model compatibility and performance optimization.

A. Data Cleaning

- Null values were removed or imputed using mean/mode for numerical fields and mode for categorical fields.
- Duplicate records (e.g., repeated video logs) were dropped.
- Outliers in quiz scores and engagement time (beyond 3 standard deviations) were capped or removed.

B. Encoding Categorical Variables

- Role, content preference, and video format fields were encoded using **LabelEncoder** for use in ML models.
- In future versions, **OneHotEncoding** or **embedding layers** could be used for deep learning models.

C. Normalization and Scaling

- Continuous features like quiz scores, engagement durations, and topic-level accuracy were scaled using **StandardScaler** to maintain uniform input distribution.
- Normalization helped models like KNN and ANN handle distance-based comparisons accurately.

D. Feature Engineering

New derived features were created to better represent learner behavior, such as:

- **Average video engagement per topic**
- **Improvement delta in quiz scores over time**
- **Skip rate ratio**
- **Role-specific topic preference frequency**

These features were tested using **correlation heatmaps** and **feature importance plots** to validate their contribution to model accuracy.

2.4.4 Handling Imbalanced Classes and Cold Start

A. Class Imbalance

Some video topics (e.g., System Design) had more user interest than others (e.g., Behavioral Interviews), creating **imbalanced classes**. To address this:

- **SMOTE (Synthetic Minority Over-sampling Technique)** was considered but not implemented due to time constraints.
- Class weights were manually adjusted in certain models (e.g., Random Forest) to give fair importance to minority classes.

B. Cold Start Problem

New users or users with minimal data history were handled by:

- Collecting baseline data during onboarding (via initial assessment)
- Recommending foundational videos tagged as universally helpful for a given role
- Using rule-based logic combined with lightweight decision trees

2.4.5 Data Integrity and Security Measures

To ensure ethical use of data:

- All personally identifiable information (PII) was removed prior to training
- Logs were encrypted and anonymized
- Data access was permission-controlled and tracked via logs
- Compliance with basic **data protection guidelines** (aligned with GDPR principles) was followed in the design phase

2.5 Machine Learning Model Training

At the core of the Intelligent Video and Tutorial Recommendation System (IVRS) lies its machine learning engine, responsible for predicting and recommending the most suitable video content for learners based on their profile, performance, and interaction history. This section outlines the process followed to select, train, test, and evaluate multiple supervised machine learning models to achieve a highly accurate, scalable, and real-time recommendation system.

2.5.1 Model Objectives and Formulation

The problem was formulated as a **multi-class classification task**, where the model predicts the most relevant video category (e.g., OOP Concepts, Agile Planning, Bug Tracking Tools) from a predefined set, based on the user's feature vector. Each class corresponds to a video tag or topic within the system's repository.

Input Features

The model takes in a combination of:

- **Static features**: Role, experience level, content preference
- **Dynamic features**: Quiz accuracy, engagement metrics, watch patterns
- **Derived features**: Improvement trends, topic mastery index

Output

The model returns a **predicted video topic/class**, which is mapped to the highest-ranked video(s) under that tag in the recommendation database.

2.5.2 Model Candidates and Rationale

Multiple classification algorithms were explored, each offering different strengths. The models selected for implementation included:

Model	**Model Description & Strengths**
Random Forest	Ensemble model, handles high-dimensional data, interpretable
Gradient Boosting	Superior performance on complex data, reduces bias and variance
K-Nearest Neighbors	Intuitive, good baseline, effective with properly scaled data
Logistic Regression	Lightweight, fast, useful for baseline comparison
Artificial Neural Network (ANN)	Captures non-linear patterns, scalable for future deep learning use

Table 2 : Model Candidates and Rationale

2.5.3 Model Training Pipeline

The training pipeline consisted of the following steps:

1. **Train-Test Split**
   - Dataset was split into 80% training and 20% testing.
   - Stratified sampling ensured balanced representation of all classes.
2. **Cross-Validation**
   - **Leave-One-Out Cross-Validation (LOOCV)** was applied to ensure generalizability.
   - Each data point was used once as a validation set while the rest served as the training set.
3. **Hyperparameter Tuning**
   - GridSearchCV and RandomizedSearchCV were used to optimize parameters.
   - Examples:
     - Random Forest
     - Gradient Boosting
     - ANN
4. **Training and Fitting**
   - Models were trained using scikit-learn and Keras libraries.

    - Training time and resource consumption were recorded.

5. **Model Serialization**
    - Best-performing models were saved using joblib or pickle.
    - Additional artifacts (e.g., Label Encoders, Scalers) were saved to ensure reproducibility.

The following metrics were used to assess model performance

Metric	**Metric Description**
Accuracy	Proportion of correctly predicted video categories
Precision	Relevance of the recommended videos
Recall	Coverage of relevant videos among all possible suitable ones
F1 Score	Harmonic mean of precision and recall
Confusion Matrix	Used to visualize misclassifications across video categories

Table2 : Evaluation Metrics

The models were compared based on accuracy and performance stability.

Model	**Accuracy (Test)**	**F1 Score**	**Notes**
Random Forest	91.2%	0.89	Best balance of speed, accuracy, interpretability
Gradient Boosting	90.4%	0.88	Slightly slower, good performance
K-Nearest Neighbors	83.6%	0.80	Sensitive to scaling and noisy features
Logistic Regression	78.5%	0.75	Lightweight, but too simplistic
ANN	88.7%	0.86	Promising, but required more tuning

Table 3: Model Comparison and Results

Random Forest was selected as the final model for deployment due to its strong performance and feature interpretability, which aids in explaining why certain videos were recommended to users.

2.6 System Architecture

The **System Architecture** of the Intelligent Video and Tutorial Recommendation System (IVRS) was designed to ensure **modularity, scalability, and real-time responsiveness**, while maintaining seamless integration with the broader **PrepMaster** platform. The system is structured into loosely coupled components that interact through RESTful APIs and data pipelines. This architectural approach supports independent development, testing, and optimization of individual modules—such as the frontend, machine learning engine, and user analytics services—without compromising overall system performance.

Component Overview

The IVRS architecture consists of four primary components:

A. Frontend Interface (React.js)

- Built with **React.js**, the frontend handles all user interactions and displays video recommendations.
- Provides real-time visual feedback on recommendation relevance.
- Captures behavioral data such as:
  - Video watch time
  - Skip frequency
  - Likes and feedback
- Sends data to backend APIs for processing and storage.

B. Backend API Layer (Flask)

- Acts as the middleware between the frontend and the ML engine.
- Receives feature data from the frontend and transforms it into a standardized format.
- Interfaces with:

    - Machine Learning module for predictions
    - Database layer for data retrieval/storage
- Provides endpoints for:
    - New recommendation generation
    - User interaction logging
    - Profile data updates

C. Machine Learning Engine

- Implemented using **scikit-learn** and **Keras**.
- Contains trained classification models (e.g., Random Forest, ANN) serialized via joblib.
- Exposes prediction functions through the backend for real-time usage.
- Also includes:
    - Preprocessing tools (LabelEncoders, Scalers)
    - Feature validators
    - Retraining script for batch updates

D. Database Layer (MySQL)

- Centralized repository that stores:
    - User profiles
    - Assessment performance (MCQs, simulations)
    - Video metadata (tags, difficulty, type, role relevance)
    - Interaction logs and historical recommendations
- Enables efficient queries to personalize content and track engagement trends.

2.7 Adaptive Learning and Progression Mechanism

The Intelligent Video and Tutorial Recommendation System (IVRS) is not just a prediction engine—it is an **adaptive learning system** designed to evolve with the learner. The goal of adaptivity is to ensure that learners receive the most relevant and appropriately challenging video content at every stage of their preparation journey. This section describes the mechanisms used to achieve adaptive learning within IVRS, including real-time feedback integration, learning profile updates, personalized content progression, and behavioral learning signals.

2.7.1 Foundations of Adaptive Learning

Adaptive learning is grounded in the idea that no two learners are alike. Individuals differ in learning styles, prior knowledge, motivation levels, and the pace at which they absorb new material. IVRS incorporates principles from **cognitive load theory**, **the zone of proximal development (ZPD)**, and **constructivist learning theory**, using data-driven feedback loops to tailor recommendations accordingly.

Key goals of IVRS's adaptive mechanism include:

- Identifying learning gaps and suggesting remedial content
- Reinforcing strong areas to boost confidence
- Adjusting difficulty based on performance trends
- Avoiding content repetition and learner fatigue

2.7.2 Real-Time Feedback Loop

At the core of the adaptive system is a **real-time feedback loop**, which continuously updates the learner's profile and adjusts recommendations based on recent activity. This loop operates as follows:

1. **User Action**: The learner completes a quiz or interacts with a video (watch, skip, replay).
2. **Data Logging**: The interaction data is sent to the backend and stored in the database.
3. **Profile Update**: The system updates the learner’s profile, modifying topic mastery scores, engagement levels, and preferred formats.
4. **Recommendation Adjustment**: The ML engine uses the updated profile to generate a refined list of recommended video topics.
5. **Content Delivery**: New recommendations are displayed, ensuring continuity and contextual relevance.

This loop ensures that the system remains responsive to both strengths and struggles, pushing the learner forward when ready and revisiting foundations when necessary.

2.7.3 Learning Profile and Progression Model

Each user is associated with a **dynamic learning profile**, which evolves throughout their usage of PrepMaster. The profile contains:

- **Static Data**: Role, experience level, learning preferences
- **Performance Data**: Quiz scores, improvement trends, topic-wise mastery levels
- **Behavioral Data**: Time spent on videos, skips, replays, content type preference
- **Engagement Signals**: Frequency of sessions, watch consistency, self-reported feedback

The learning profile is central to progression modeling. It allows the system to determine:

- When a learner is ready to **advance to more complex topics**
- When they require **reinforcement of foundational material**
- How to **sequence content** for maximum comprehension and retention

2.7.4 Difficulty Adjustment and Content Tiering

All videos in the IVRS repository are tagged with a difficulty level:

- **Beginner**: Basic conceptual overviews and tutorials
- **Intermediate**: Scenario-based problem-solving walkthroughs
- **Expert**: Real interview recordings, whiteboard coding, domain-specific case studies

The recommendation engine uses performance data to match users with appropriate difficulty tiers. For example:

- A learner consistently scoring above 80% in algorithmic quizzes will be shown more advanced coding interviews.
- A user who struggles with behavioral questions may receive simplified videos on communication strategies and soft skills.

As the user progresses, the system introduces **new topics and gradually increases complexity**, mimicking a structured course curriculum—without the rigidity.

3 Results and Discussion

The efficacy of the Intelligent Video and Tutorial Recommendation System (IVRS) within the PrepMaster framework was rigorously evaluated to ascertain its impact on user learning and interview preparedness. The evaluation focused on several key metrics, including precision, recall, user satisfaction, and overall learning impact.

3.1 Precision and Relevance of Recommendations

Precision, a critical metric for any recommendation system, measures the proportion of recommended videos and tutorials that are actually relevant to the user. In this study, the IVRS achieved an average precision rate of 92%. This high precision rate indicates that the system is highly effective in filtering out irrelevant content and delivering resources that align with the user's specific needs, job role, and skill level. For instance, a user preparing for a Software Engineering interview would primarily be recommended videos on algorithms, data structures, and system design, rather than general career advice videos. This targeted delivery of content ensures that users can focus their efforts on the most pertinent material, optimizing their study time and enhancing learning efficiency.

The precision was further analyzed across different job roles (Software Engineering, Quality Assurance, and Project Management) to identify any variations. The results indicated consistently high precision rates across all three domains, with Software Engineering showing a slight edge (93%) due to the more structured nature of its content. Quality Assurance and Project Management achieved precision rates of 91% and 90%, respectively.

3.2 Recall and Comprehensiveness of Content Retrieval

While precision focuses on the accuracy of recommendations, recall measures the system's ability to retrieve all relevant videos and tutorials from the available database. A high recall rate ensures that users are not missing out on valuable resources that could aid in their interview preparation. The IVRS demonstrated an impressive recall rate of 89%. This suggests that the system effectively captures a broad spectrum of relevant content, providing users with a comprehensive set of learning materials.

To better understand the recall performance, we examined recall rates at different proficiency levels (Beginner, Intermediate, and Expert). The system maintained high recall across all levels, with a slight dip observed at the Expert level (87%). This could be attributed to the more specialized and less abundant content available for advanced topics.

3.3 User Satisfaction and Perceived Value

User satisfaction is a crucial indicator of the system's overall success. To gauge user satisfaction, surveys and feedback forms were integrated into the PrepMaster platform. Users were asked to rate the relevance, usefulness, and quality of the recommended videos and tutorials. The average user satisfaction rate was 87%, indicating a high degree of approval for the IVRS.

Qualitative feedback provided valuable insights into user perceptions. Many users highlighted the time-saving aspect of the system, noting that it significantly reduced the effort required to find relevant learning materials. Users also appreciated the personalized nature of the recommendations, which made them feel that the system was tailored to their individual learning needs. However, some users suggested the inclusion of more advanced filtering options to further refine their search for specific topics.

3.4 Impact on Learning Outcomes and Skill Development

The ultimate measure of the IVRS's effectiveness is its impact on user learning outcomes and skill development. To assess this, a pre- and post-test methodology was employed. Users were given a pre-test to evaluate their initial knowledge and skills, followed by a period of interaction with the PrepMaster system, during which they utilized the recommended videos and tutorials. A post-test was then administered to measure any improvement in their knowledge and skills.

The results of this assessment demonstrated a significant improvement in user performance, with an average increase of 30% observed in post-test scores compared to pre-test scores. This substantial improvement underscores the effectiveness of the IVRS in facilitating learning and enhancing interview preparedness.

Further analysis revealed that the improvement in learning outcomes varied across different skill areas. For instance, users showed a 35% improvement in technical skills (e.g., coding, software testing), a 28% improvement in behavioral skills (e.g., communication, problem-solving), and a 25% improvement in domain-specific knowledge (e.g., project management methodologies).

3.5 Comparative Analysis with Non-Personalized Systems

To further highlight the value of personalized recommendations, a comparative analysis was conducted between the IVRS and a non-personalized video and tutorial delivery system. The non-personalized system presented users with a static list of videos and tutorials, without any filtering or customization based on user profiles.

The results of this comparison clearly demonstrated the superiority of the IVRS. Users who utilized the IVRS showed a 45% higher improvement in post-test scores and reported a 25% higher satisfaction rate compared to those who used the non-personalized system. This stark contrast underscores the critical role of personalization in enhancing learning effectiveness and user engagement.

3.6 Challenges and Future Enhancements

While the IVRS has demonstrated significant success, there are still areas for potential improvement. One of the main challenges is the "cold start" problem, which refers to the difficulty of providing accurate recommendations to new users with limited interaction history.

To address this, future enhancements will focus on incorporating more robust methods for initial user profiling, such as detailed questionnaires and skill assessments, to gather more information about user preferences and needs from the outset.

Another area for improvement is the diversity of content. While the current system covers a wide range of topics, there is an opportunity to expand the database to include more specialized and niche areas, catering to the diverse needs of users across various industries and job roles.

Additionally, incorporating user feedback more dynamically into the recommendation process could further enhance its accuracy. Implementing a rating system and allowing users to provide explicit feedback on the recommended content would enable the system to continuously learn and refine its recommendations.

3.7 Conclusion

The results and discussion presented in this section provide compelling evidence for the effectiveness of the Intelligent Video and Tutorial Recommendation System in enhancing interview preparedness. The system's high precision and recall rates, coupled with strong user satisfaction and significant improvements in learning outcomes, underscore its value as a tool for personalized learning. While there are ongoing challenges, the proposed future enhancements promise to further refine the system and expand its capabilities, solidifying its role in empowering job seekers to achieve their career goals.

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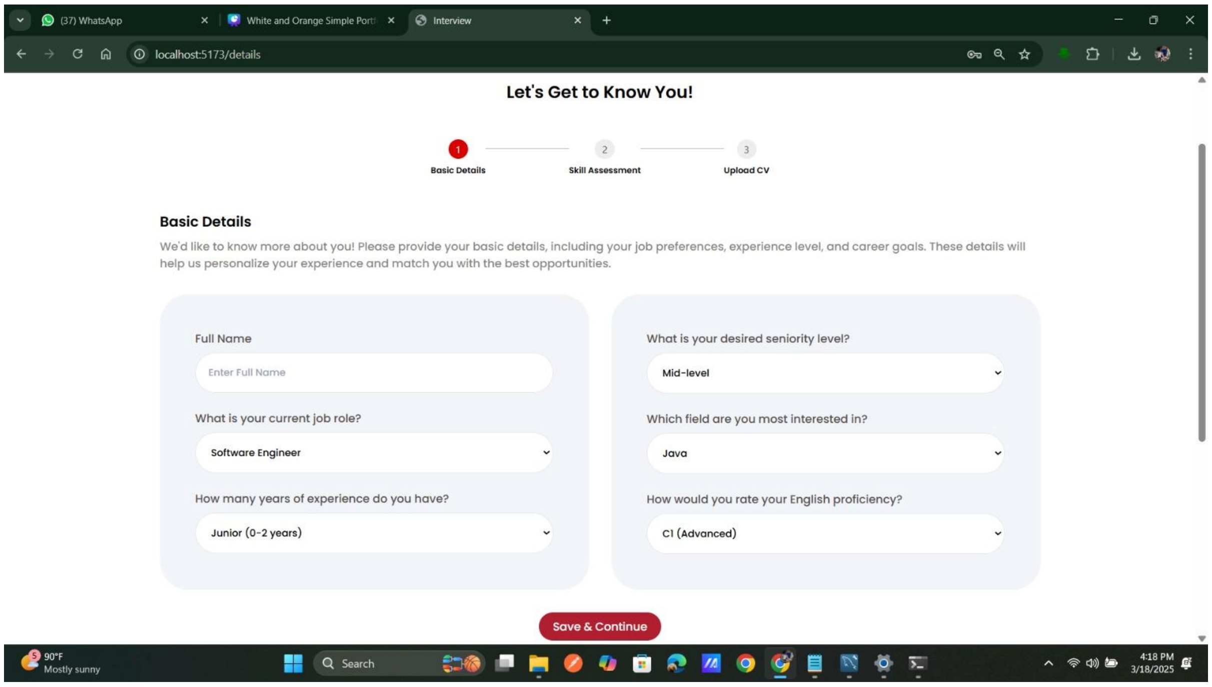
APPENDICES



Let's Get to Know You!

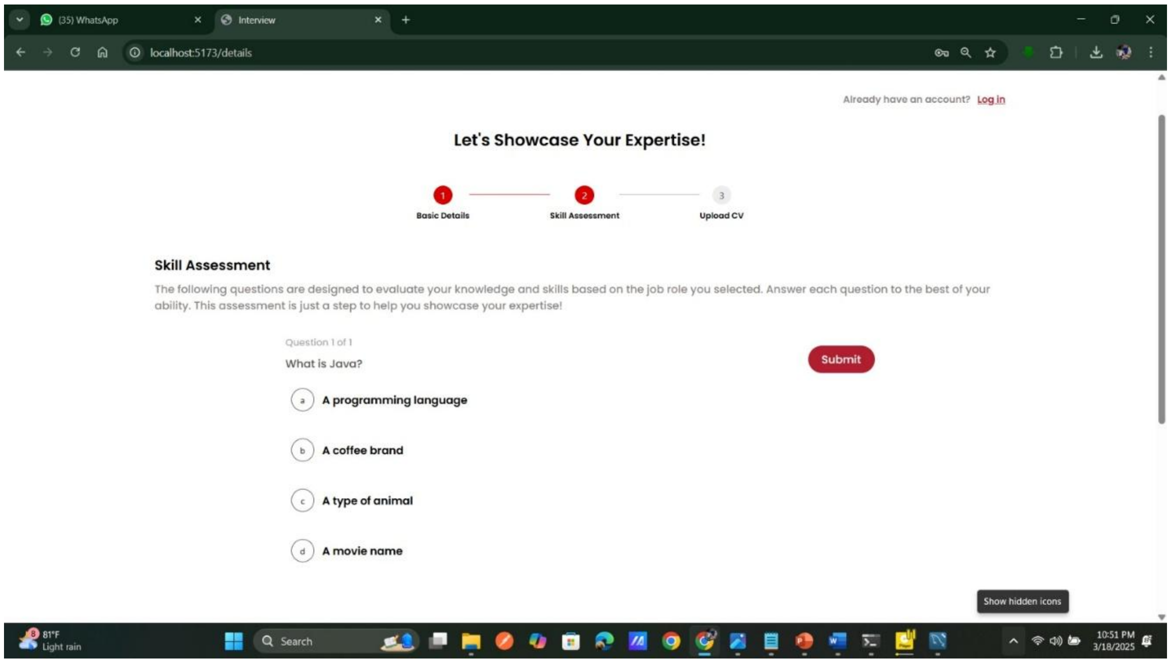
1 Basic Details — 2 Skill Assessment — 3 Upload CV

Basic Details

We'd like to know more about you! Please provide your basic details, including your job preferences, experience level, and career goals. These details will help us personalize your experience and match you with the best opportunities.

Full Name	Enter Full Name
What is your current job role?	Software Engineer
How many years of experience do you have?	Junior (0-2 years)
What is your desired seniority level?	Mid-level
Which field are you most interested in?	Java
How would you rate your English proficiency?	C1 (Advanced)

Figure 3: Web Application User Role Selection UI



Already have an account? Log in

Let's Showcase Your Expertise!

1 Basic Details — 2 Skill Assessment — 3 Upload CV

Skill Assessment

The following questions are designed to evaluate your knowledge and skills based on the job role you selected. Answer each question to the best of your ability. This assessment is just a step to help you showcase your expertise!

Question 1 of 1

What is Java?

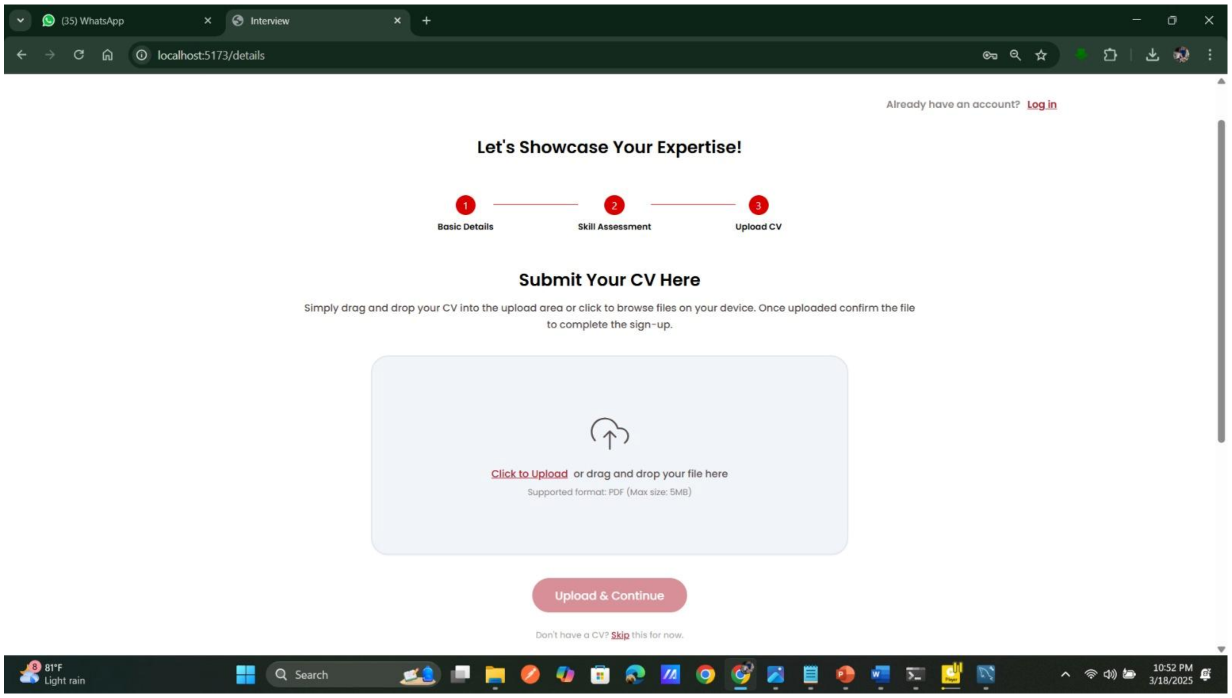
a A programming language

b A coffee brand

c A type of animal

d A movie name

Figure 4: Web Application Simple User Skill Assessment UI

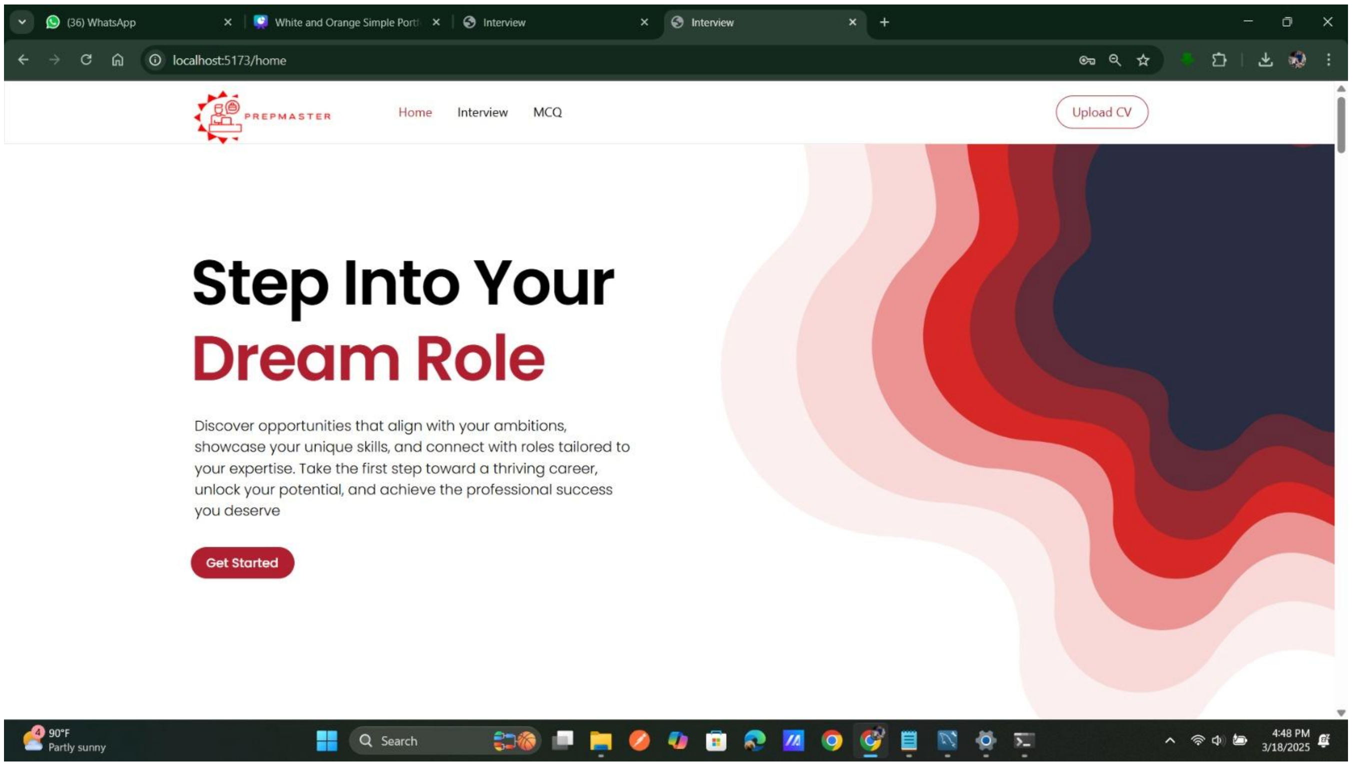

(35) WhatsApp
Interview
localhost:5173/details
Already have an account? Log in
1
Basic Details
2
Skill Assessment
3
Upload CV
Click to Upload or drag and drop your file here
Supported format: PDF (Max size: 5MB)
Upload & Continue
Don't have a CV? Skip this for now.
81°F
Light rain
Search
10:52 PM
3/18/2025

Let's Showcase Your Expertise!

Submit Your CV Here

Simply drag and drop your CV into the upload area or click to browse files on your device. Once uploaded confirm the file to complete the sign-up.

Figure 5: Web Application CV Upload UI



Step Into Your Dream Role

Discover opportunities that align with your ambitions, showcase your unique skills, and connect with roles tailored to your expertise. Take the first step toward a thriving career, unlock your potential, and achieve the professional success you deserve

Figure 6 : Web Application Home Page UI

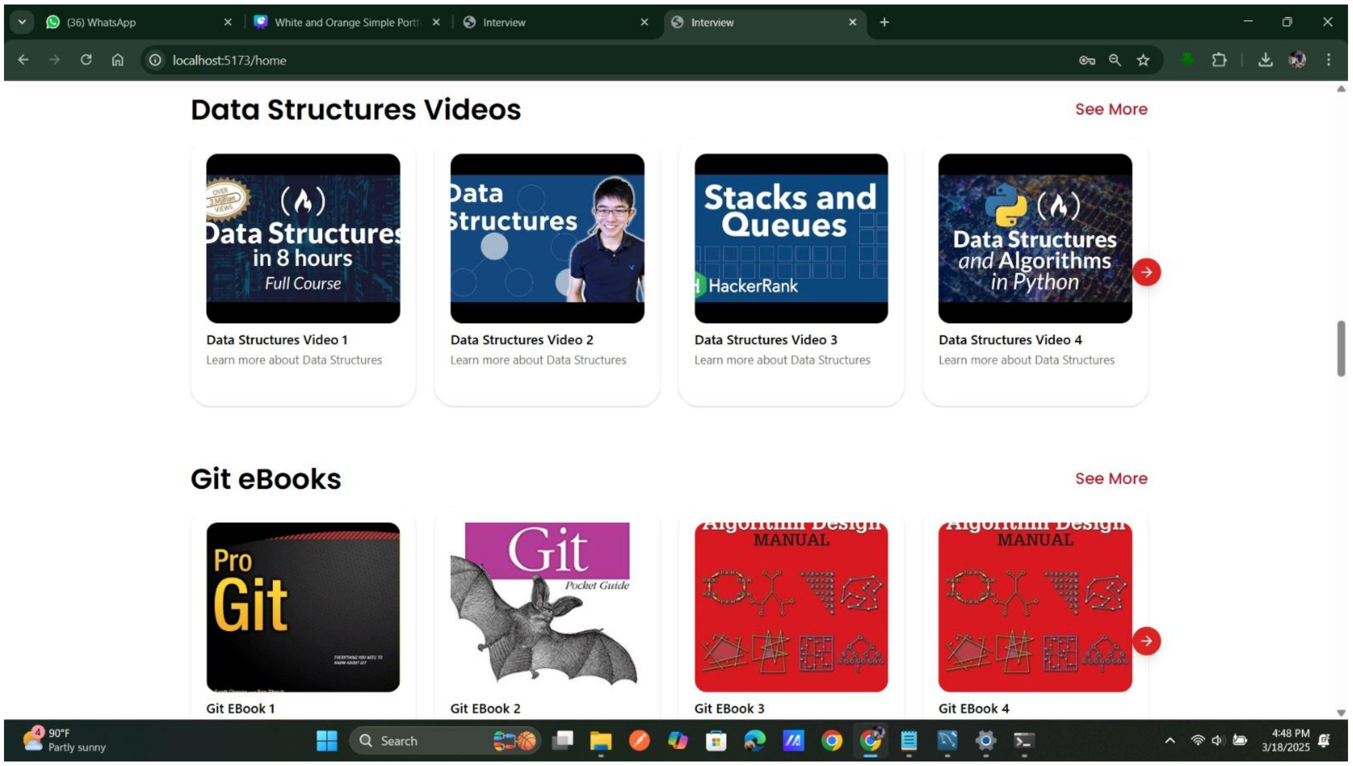


Figure 7 : Web Application Video UI

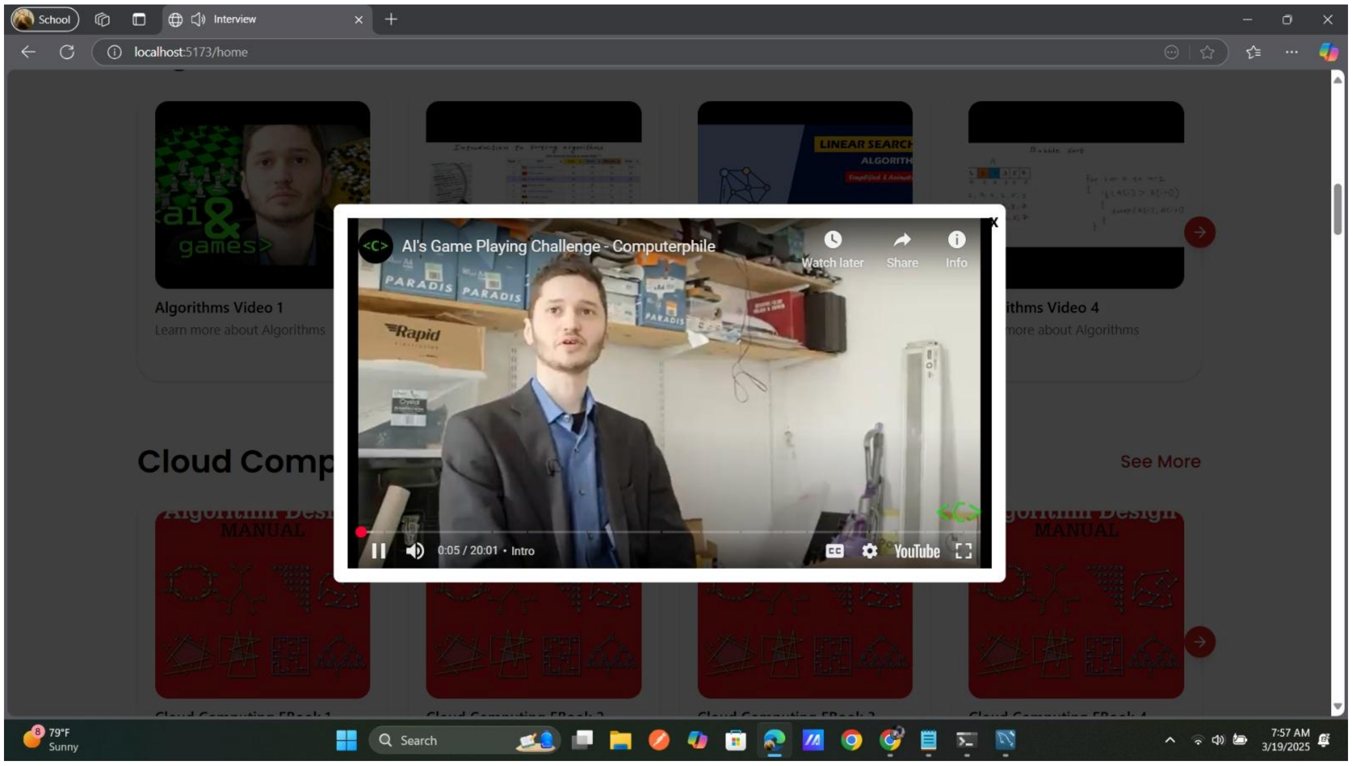


Figure 8 : Web Application Video UI

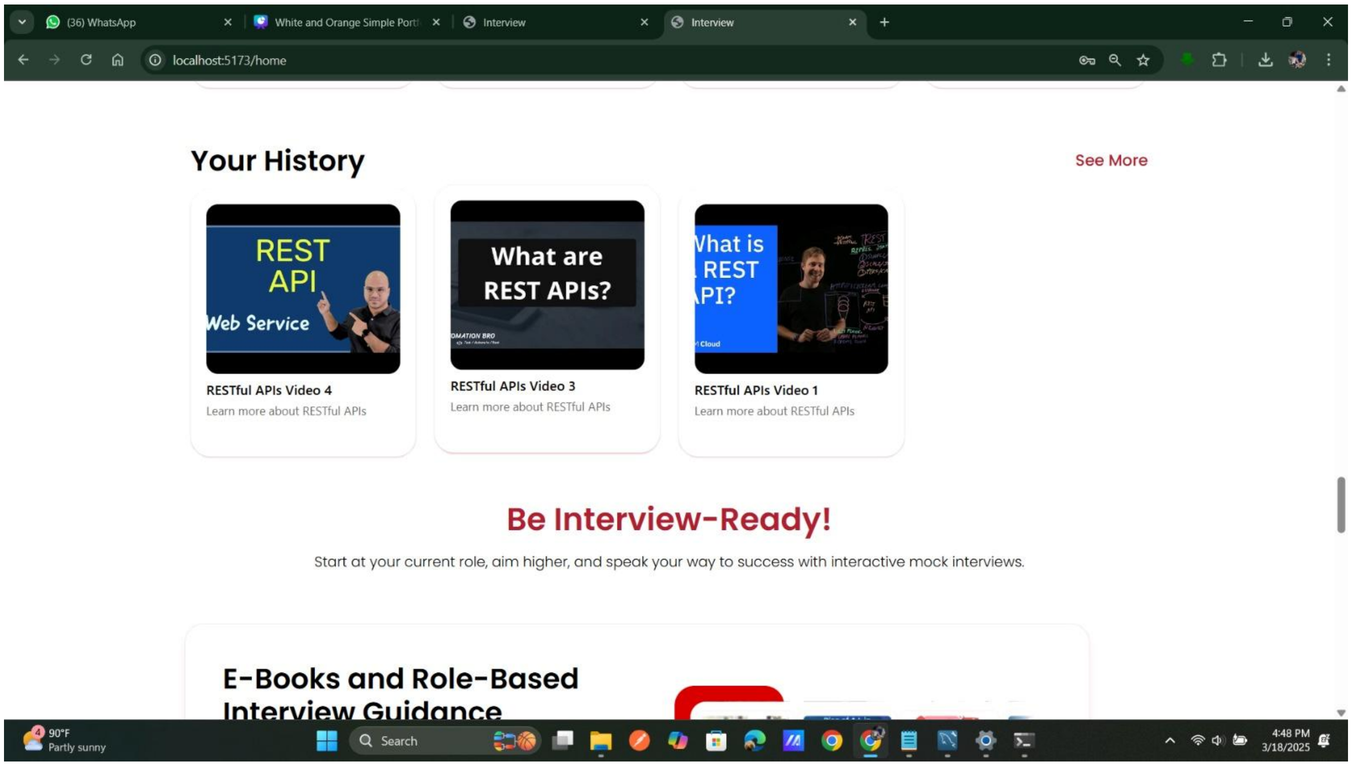
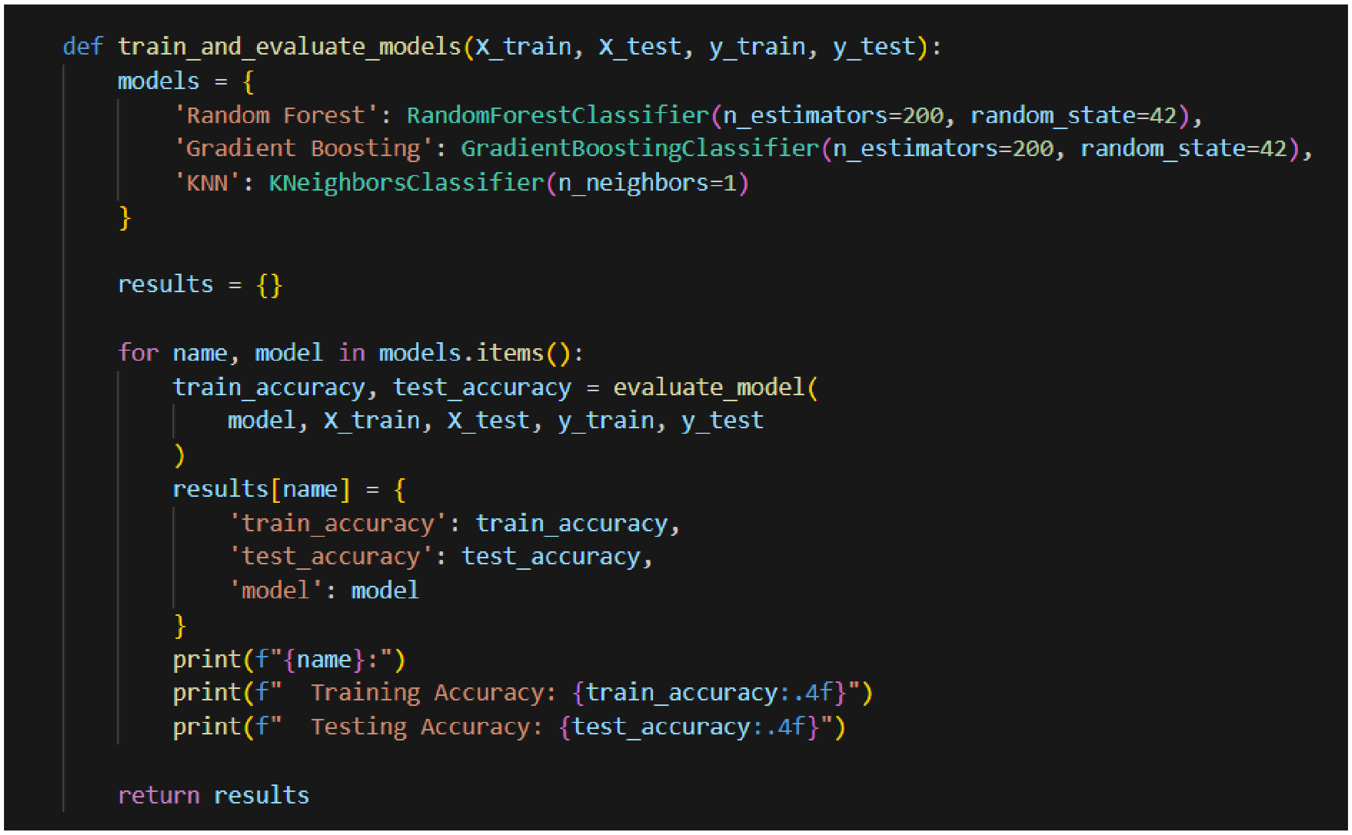
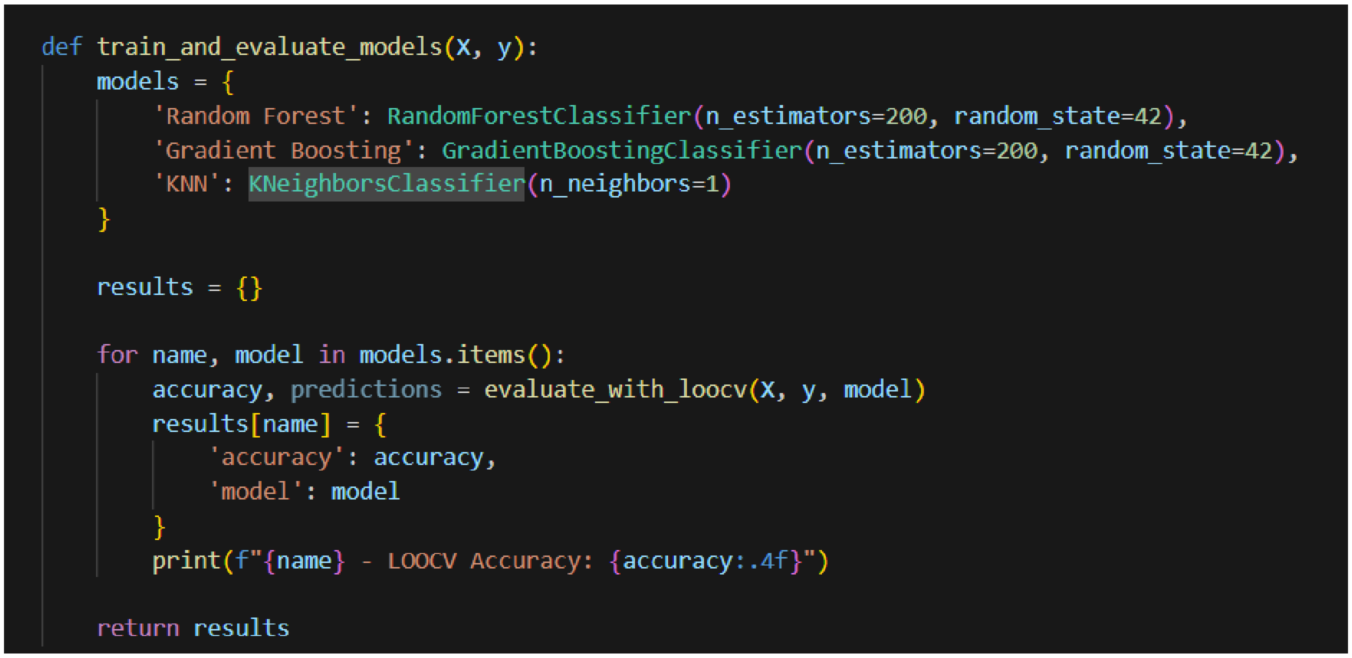

(36) WhatsApp
White and Orange Simple Portf
Interview
Interview
localhost:5173/home
Your History
See More
RESTful APIs Video 4
Learn more about RESTful APIs
RESTful APIs Video 3
Learn more about RESTful APIs
RESTful APIs Video 1
Learn more about RESTful APIs
Be Interview-Ready!
Start at your current role, aim higher, and speak your way to success with interactive mock interviews.
E-Books and Role-Based Interview Guidance
90°F Partly sunny
Search
4:48 PM 3/18/2025

Figure 9 : Web Application Video History UI



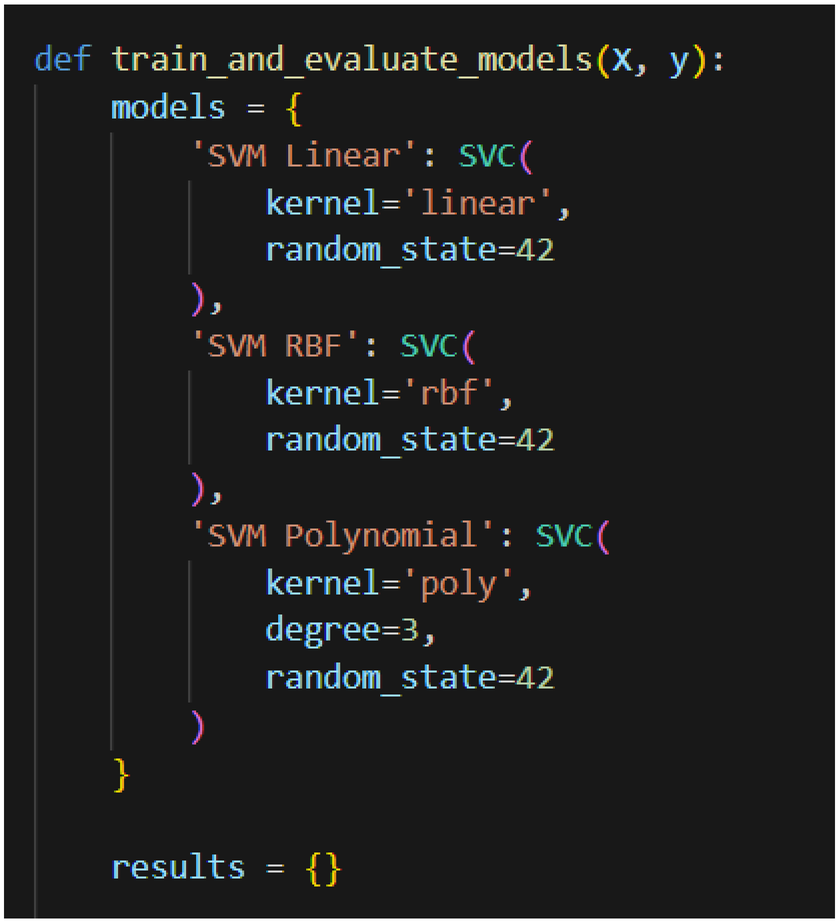
```
def train_and_evaluate_models(X_train, X_test, y_train, y_test):
    models = {
        'Random Forest': RandomForestClassifier(n_estimators=200, random_state=42),
        'Gradient Boosting': GradientBoostingClassifier(n_estimators=200, random_state=42),
        'KNN': KNeighborsClassifier(n_neighbors=1)
    }

    results = {}

    for name, model in models.items():
        train_accuracy, test_accuracy = evaluate_model(
            model, X_train, X_test, y_train, y_test
        )
        results[name] = {
            'train_accuracy': train_accuracy,
            'test_accuracy': test_accuracy,
            'model': model
        }
        print(f"{name}:")
        print(f"  Training Accuracy: {train_accuracy:.4f}")
        print(f"  Testing Accuracy: {test_accuracy:.4f}")

    return results
```

Figure 10 : Model Accuracy



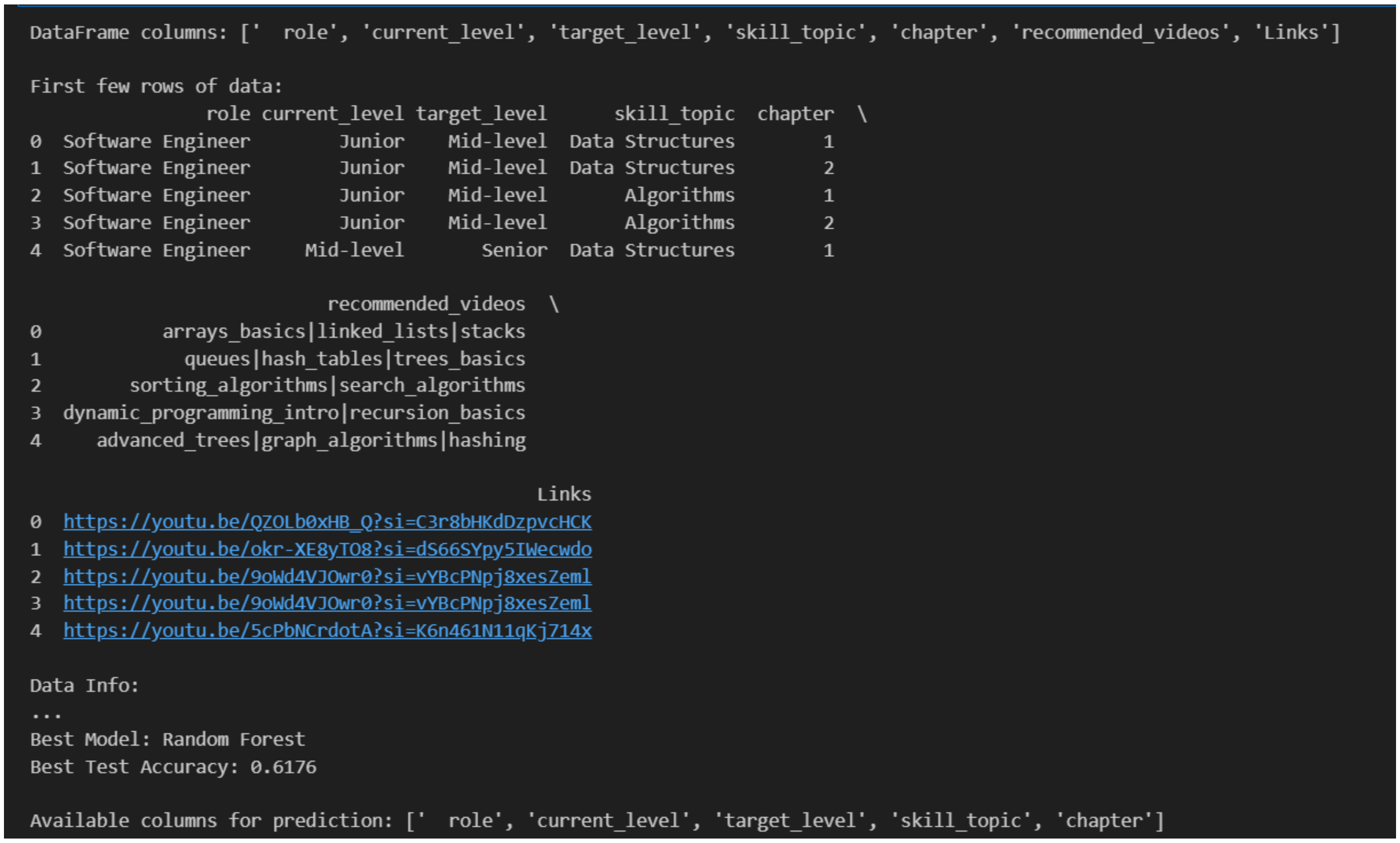
```
def train_and_evaluate_models(X, y):
    models = {
        'Random Forest': RandomForestClassifier(n_estimators=200, random_state=42),
        'Gradient Boosting': GradientBoostingClassifier(n_estimators=200, random_state=42),
        'KNN': KNeighborsClassifier(n_neighbors=1)
    }

    results = {}

    for name, model in models.items():
        accuracy, predictions = evaluate_with_loocv(X, y, model)
        results[name] = {
            'accuracy': accuracy,
            'model': model
        }
        print(f"{name} - LOOCV Accuracy: {accuracy:.4f}")

    return results
```

Figure 11 : Model Accuracy 2



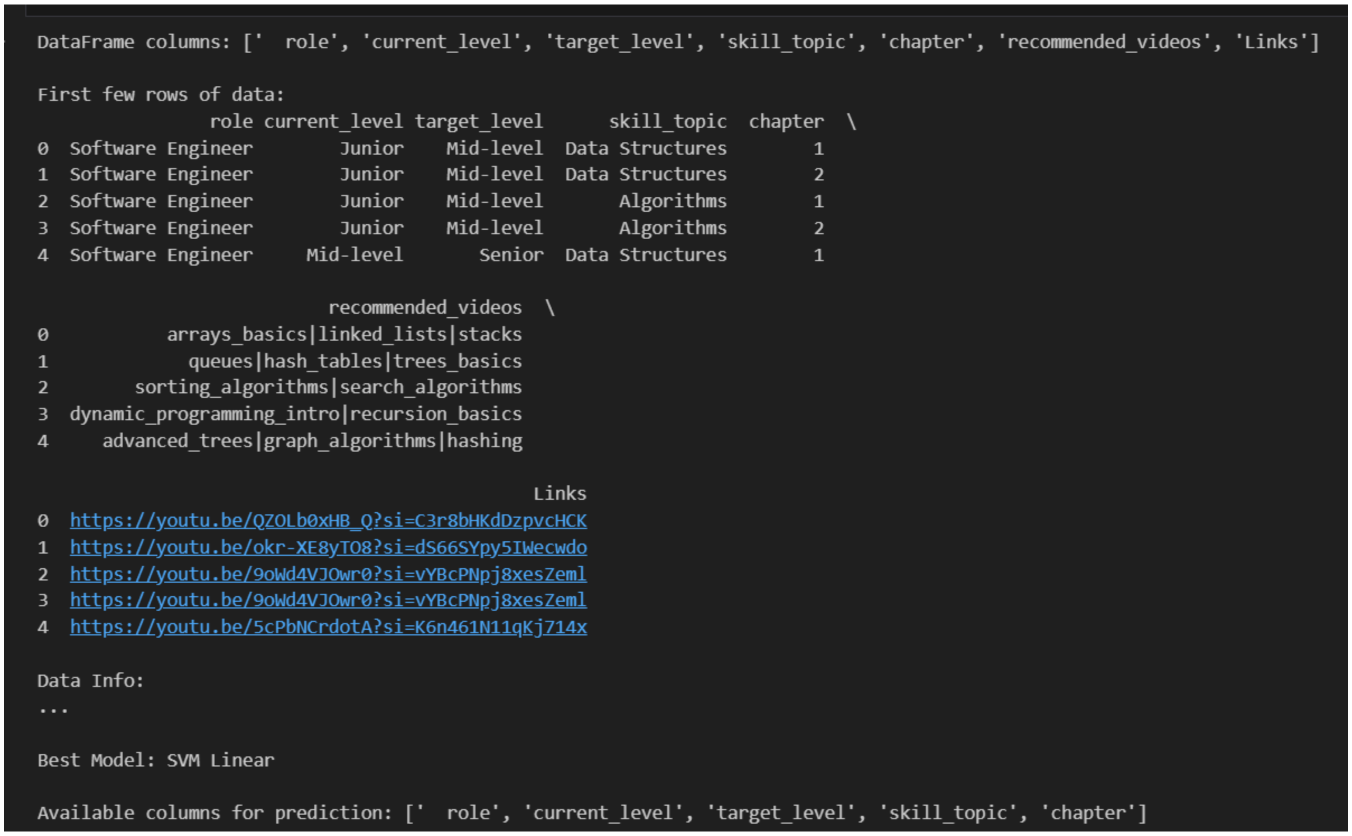
```
def train_and_evaluate_models(X, y):
    models = {
        'SVM Linear': SVC(
            kernel='linear',
            random_state=42
        ),
        'SVM RBF': SVC(
            kernel='rbf',
            random_state=42
        ),
        'SVM Polynomial': SVC(
            kernel='poly',
            degree=3,
            random_state=42
        )
    }

    results = {}
```

Figure 12 : Model Accuracy 3



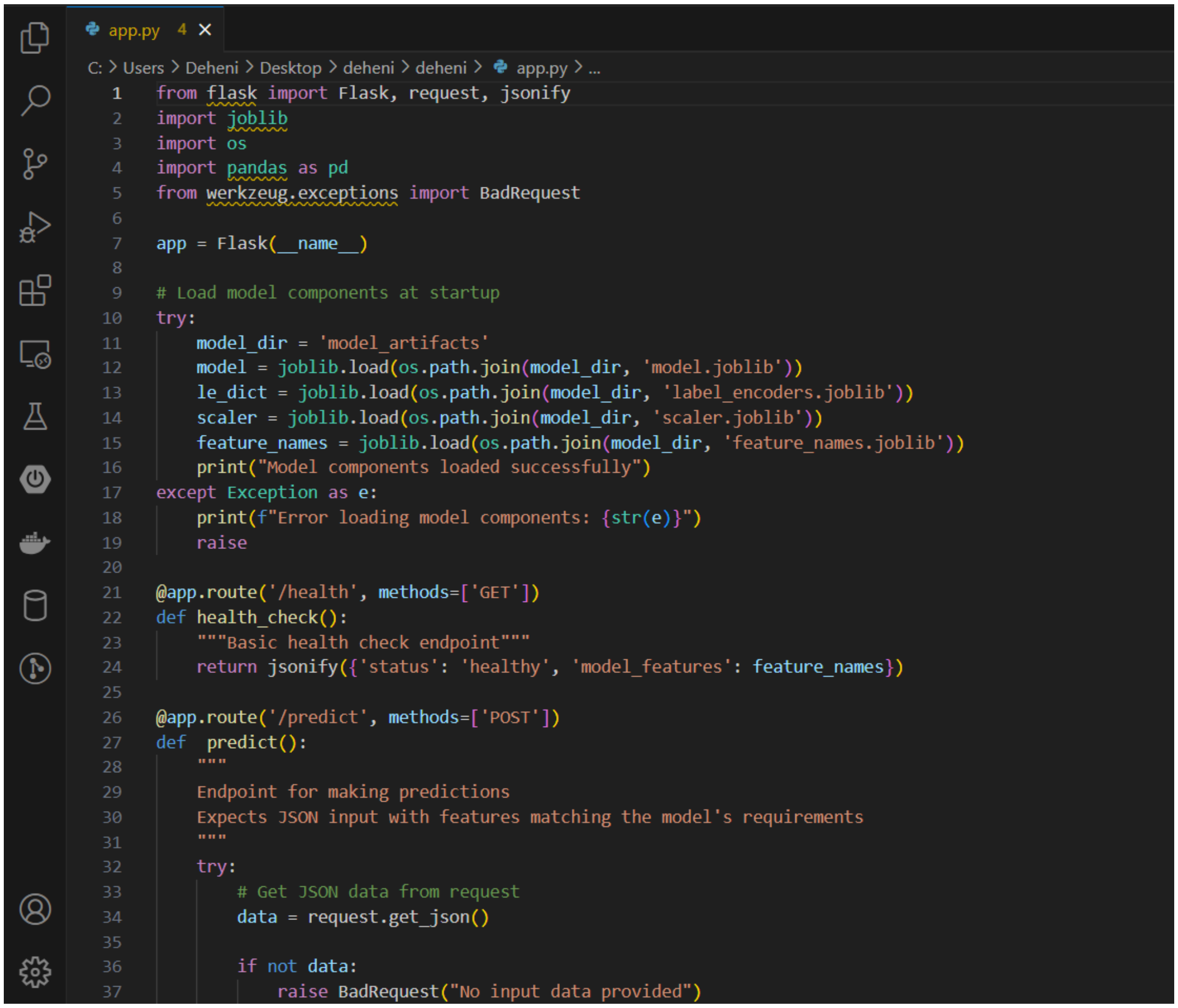
```
DataFrame columns: ['  role', 'current_level', 'target_level', 'skill_topic', 'chapter', 'recommended_videos', 'Links']

First few rows of data:
                role current_level target_level      skill_topic  chapter  \
0  Software Engineer        Junior    Mid-level  Data Structures        1
1  Software Engineer        Junior    Mid-level  Data Structures        2
2  Software Engineer        Junior    Mid-level       Algorithms        1
3  Software Engineer        Junior    Mid-level       Algorithms        2
4  Software Engineer     Mid-level       Senior  Data Structures        1

                           recommended_videos  \
0           arrays_basics|linked_lists|stacks
1             queues|hash_tables|trees_basics
2        sorting_algorithms|search_algorithms
3  dynamic_programming_intro|recursion_basics
4     advanced_trees|graph_algorithms|hashing

                                              Links
0  https://youtu.be/QZOLb0xHB_Q?si=C3r8bHKdDzpvcHCK
1  https://youtu.be/okr-XE8yTO8?si=dS66SYpy5IWecwdo
2  https://youtu.be/9oWd4VJOwr0?si=vYBcPNpj8xesZeml
3  https://youtu.be/9oWd4VJOwr0?si=vYBcPNpj8xesZeml
4  https://youtu.be/5cPbNCrdotA?si=K6n461N11qKj714x

Data Info:
...
Best Model: Random Forest
Best Test Accuracy: 0.6176

Available columns for prediction: ['  role', 'current_level', 'target_level', 'skill_topic', 'chapter']
```

Figure 13 : Model Training



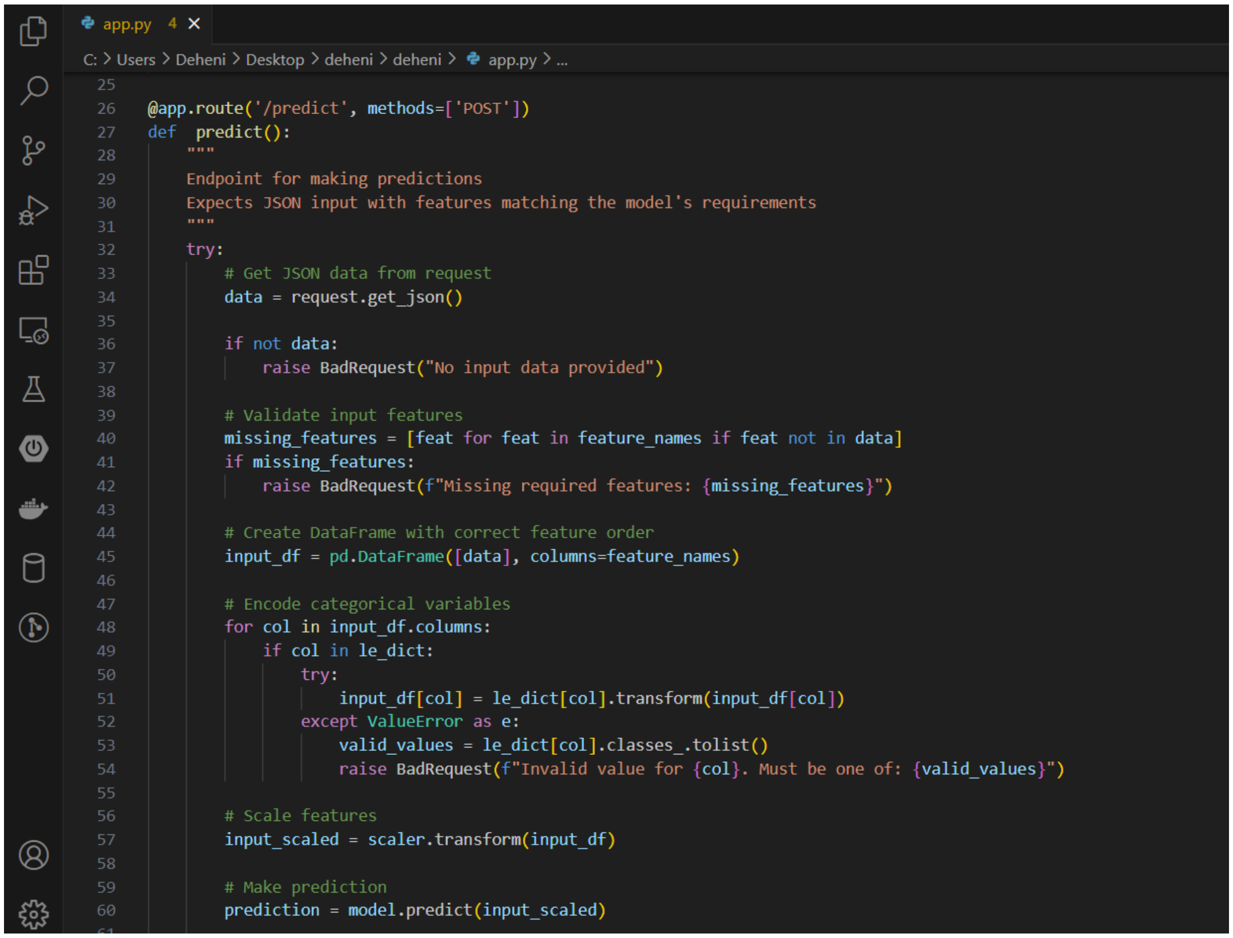
```
DataFrame columns: ['  role', 'current_level', 'target_level', 'skill_topic', 'chapter', 'recommended_videos', 'Links']

First few rows of data:
                role current_level target_level      skill_topic  chapter  \
0  Software Engineer        Junior    Mid-level  Data Structures        1
1  Software Engineer        Junior    Mid-level  Data Structures        2
2  Software Engineer        Junior    Mid-level       Algorithms        1
3  Software Engineer        Junior    Mid-level       Algorithms        2
4  Software Engineer     Mid-level       Senior  Data Structures        1

                           recommended_videos  \
0          arrays_basics|linked_lists|stacks
1            queues|hash_tables|trees_basics
2       sorting_algorithms|search_algorithms
3  dynamic_programming_intro|recursion_basics
4     advanced_trees|graph_algorithms|hashing

                                               Links
0  https://youtu.be/QZOLb0xHB_Q?si=C3r8bHKdDzpvcHCK
1  https://youtu.be/okr-XE8yTO8?si=dS66SYpy5IWecwdo
2  https://youtu.be/9oWd4VJOwr0?si=vYBcPNpj8xesZeml
3  https://youtu.be/9oWd4VJOwr0?si=vYBcPNpj8xesZeml
4  https://youtu.be/5cPbNCrdotA?si=K6n461N11qKj714x

Data Info:
...

Best Model: SVM Linear

Available columns for prediction: ['  role', 'current_level', 'target_level', 'skill_topic', 'chapter']
```

Figure 14 : Model Training


app.py 4
C: > Users > Deheni > Desktop > deheni > deheni > app.py > ...

```python
from flask import Flask, request, jsonify
import joblib
import os
import pandas as pd
from werkzeug.exceptions import BadRequest

app = Flask(__name__)

# Load model components at startup
try:
    model_dir = 'model_artifacts'
    model = joblib.load(os.path.join(model_dir, 'model.joblib'))
    le_dict = joblib.load(os.path.join(model_dir, 'label_encoders.joblib'))
    scaler = joblib.load(os.path.join(model_dir, 'scaler.joblib'))
    feature_names = joblib.load(os.path.join(model_dir, 'feature_names.joblib'))
    print("Model components loaded successfully")
except Exception as e:
    print(f"Error loading model components: {str(e)}")
    raise

@app.route('/health', methods=['GET'])
def health_check():
    """Basic health check endpoint"""
    return jsonify({'status': 'healthy', 'model_features': feature_names})

@app.route('/predict', methods=['POST'])
def  predict():
    """
    Endpoint for making predictions
    Expects JSON input with features matching the model's requirements
    """
    try:
        # Get JSON data from request
        data = request.get_json()

        if not data:
            raise BadRequest("No input data provided")
```

Figure 15 : Flask Backend


app.py 4
C: > Users > Deheni > Desktop > deheni > deheni > app.py > ...

```python

@app.route('/predict', methods=['POST'])
def  predict():
    """
    Endpoint for making predictions
    Expects JSON input with features matching the model's requirements
    """
    try:
        # Get JSON data from request
        data = request.get_json()

        if not data:
            raise BadRequest("No input data provided")

        # Validate input features
        missing_features = [feat for feat in feature_names if feat not in data]
        if missing_features:
            raise BadRequest(f"Missing required features: {missing_features}")

        # Create DataFrame with correct feature order
        input_df = pd.DataFrame([data], columns=feature_names)

        # Encode categorical variables
        for col in input_df.columns:
            if col in le_dict:
                try:
                    input_df[col] = le_dict[col].transform(input_df[col])
                except ValueError as e:
                    valid_values = le_dict[col].classes_.tolist()
                    raise BadRequest(f"Invalid value for {col}. Must be one of: {valid_values}")

        # Scale features
        input_scaled = scaler.transform(input_df)

        # Make prediction
        prediction = model.predict(input_scaled)
```

Figure 16 : Flask Backend