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SkillMesh: A peer-to-peer platform for collaborative skill exchange

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Abstract

In the digital age, skill acquisition is increasingly reliant on pre-recorded courses and generalized lectures available on platforms such as YouTube and Coursera. While these methods have become the norm, they often fail to meet the personalized learning needs of individuals. This paper introduces SkillMesh, an innovative application designed to transform how people acquire knowledge by facilitating direct connections be- tween learners and mentors. The platform offers personalized courses tailored to individual learning goals. By leveraging advanced algorithms, SkillMesh ensures a dynamic, interactive learning experience that fosters continuous skill development. This innovative approach not only enhances learning effectiveness but also builds a supportive community dedicated to personal and professional growth. Our research highlights SkillMesh's potential to transform the educational landscape by providing a scalable and adaptable solution for personalized learning in the digital era

Keywords: Skill Exchange; Community Building; Android Development; Matchmaking Algorithm

1. Introduction

In the digital age, the way individuals acquire skills is increasingly influenced by online platforms, which offer massive libraries of pre-recorded content such as courses, webinars, and tutorials. However, these platforms often struggle to meet the personalized needs of learners, as they primarily provide generalized, one-size-fits-all content. The lack of customization in these learning models limits engagement and effectiveness, as learners face difficulties in tailoring content to their individual goals or receiving real-time feedback. Furthermore, many platforms fail to establish meaningful connections between learners and mentors, leaving a gap in the mentorship and guidance that is essential for personal and professional growth.

SkillMesh addresses these challenges by offering a tailored, interactive learning environment that bridges the gap between learners and experienced mentors, promoting a more personalized and engaging approach to skill development.

2. Literature survey

2.1. A Comprehensive Survey on Online Social Networks Security and Privacy Issues: Threats, Machine Learning-Based Solutions, and Open Challenges:

Bhattacharya et al. (2024) reviewed various threats and privacy concerns within online social networks, proposing machine learning-based solutions for threat detection and mitigation. The authors emphasized that while ML can significantly enhance privacy protections, challenges remain in adapting these systems to rapidly changing social

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platforms and evolving cyber threats. Further research is needed to tackle the complexity of real-time threat detection in large-scale social networks..

2.2. Methods and Technologies for Supporting Knowledge Sharing within Learning Communities: A Systematic Literature Review (2020):

The paper systematically reviews existing literature on knowledge-sharing methods and technologies to explore how they can be used to support learning communities. It aims to identify the most effective tools, approaches, and technologies that promote collaborative learning and facilitate knowledge exchange.

2.3. Knowledge Sharing through Social Media Platforms in the Silicon Age" (2019) :

Yaqub and Alsabban provide valuable insights into the role of social media platforms in modern knowledge-sharing practices, exploring both their potential and limitations in this context. The research suggests that while social media has democratized knowledge access, there is a need for structured approaches to maximize its potential for meaningful knowledge exchange.

2.4. Digital Platforms and the Improvement of Learning Outcomes: Evidence Extracted from Meta-Analysis" by J. Doe and J. Smith (2023):

The study aggregates evidence from various research papers to evaluate the role of digital platforms in enhancing learning outcomes. It identifies key features like interactivity and accessibility as driving factors for improved engagement. However, inconsistencies in study designs and data biases limit the generalizability of its conclusions.

2.5. PCRS: Personalized Course Recommender System Based on Hybrid Approach" by Zameer Gulzar, Anny Leema and Gerard Deepak (2018) :

The paper develops a personalized course recommendation system by blending collaborative filtering with content-based methods. It successfully addresses diverse learner needs and improves accuracy. However, challenges such as the computational cost of hybridization and balancing multiple recommendation techniques persist.

2.6. Collaborative Filtering Recommendation of Online Learning Resources Based on Knowledge Association Model" by Henan Jia, Lifen Yang and Bo Cui (2023) :

This research presents a recommendation framework that integrates collaborative filtering with a knowledge association model to improve online learning resource suggestions. By leveraging user-item relationships, it delivers relevant content but requires robust datasets and faces limitations with sparsity in input data.

2.7. Deep Learning for Recommender Systems" by Alexandros Karatzoglou and Balázs Hidasi (2017) :

Discusses how deep neural networks can model complex user-item interactions more effectively than traditional methods. By leveraging techniques such as deep autoencoders, convolutional neural networks (CNNs), and recurrent neural networks (RNNs), the paper demonstrates how deep learning can enhance the prediction accuracy and personalization of recommendations. This approach helps capture non-linear relationships and intricate patterns in user behavior, paving the way for more sophisticated and effective recommendation systems.

2.8. Autoencoders for Collaborative Filtering" by Dawen Liang, Rahul G Krishnan, Matthew D Hoffman and Tony Jebara (2018) :

R. Salakhutdinov and A. Mnih presents the use of autoencoders, a type of neural network, for enhancing collaborative filtering in recommender systems. It highlights how autoencoders can learn compact, latent representations of user-item interactions to predict user preferences for unseen items. This method offers a powerful alternative to traditional matrix factorization techniques by effectively capturing complex patterns in data and handling large, sparse datasets common in recommendation scenarios.

2.9. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding" (2018):

Jacob Devlin, Ming-Wei Chang, Kenton Lee and Kristina Toutanova introduce BERT, a state-of-the-art model for natural language understanding that leverages bidirectional training of transformers to achieve superior performance in a variety of language tasks. The key takeaway is that BERT's pre-training allows it to capture deep contextual relationships within text, significantly improving the accuracy of downstream applications like question answering and sentence prediction. This breakthrough demonstrates how deep learning models can be pre-trained on large text corpora and then fine-tuned for specific tasks, setting a new standard in the field of NLP.

3. Methodology

3.1. User-Centric Skill Exchange Model

The primary focus of the system is to allow users to list, search, and exchange skills in a way that is both efficient and reliable. This model involves:.

- User-Centric Skill Exchange Model : Users can create profiles that list the skills they possess and specify the skills they wish to acquire. The system allows users to categorize their skills (e.g., technical, creative, language skills) and tag them for easy searchability. This tagging system helps with efficient indexing, allowing users to find skills that match their needs more easily.
- Dynamic Matching The system uses a heuristic-based algorithm to match users. The algorithm considers factors such as complementary skills, user availability, and proximity to find the best matches. Users can be matched based on the skills they offer and the ones they wish to acquire, ensuring both parties benefit from the exchange
- Trust Mechanisms : Feedback and peer review systems are implemented, where users can rate and review each other after completing a skill exchange. This helps build trust within the community. Reputation scores are assigned based on feedback to ensure reliability, making it easier for users to identify trustworthy individuals.

3.2. Matchmaking Algorithm

A core component of the SkillMesh application is its matchmaking algorithm, which is designed to optimize user connections for skill exchanges. The algorithm is built on the following key components:

- Data Normalization: User inputs, such as skill categories and availability, are normalized to ensure uniformity in format. This allows the system to process data more efficiently and ensure compatibility in search and recommendation processes.
- Proximity-Based Matching: The system integrates geolocation data to connect users within a predefined radius. By leveraging location services, the platform ensures that users are matched with others nearby, fostering local community building.
- Compatibility Scoring: Compatibility scores are calculated based on multiple factors, including:
    - Relevance of skills
    - User availability (scheduling)
    - Past feedback and reputation scores from previous exchanges.

This scoring system helps prioritize the most suitable matches for users, making the platform more efficient.

3.3. Feedback and Iterative Improvements:

SkillMesh integrates a continuous feedback loop to refine the system and improve user satisfaction:

- User Behavior Analysis:The platform monitors user activity to understand engagement patterns. The data is analyzed to identify areas for improvement in matchmaking, skill listing, and the overall user experience.
- Iterative Updates: The system is continuously updated based on user feedback. For example, if users indicate that certain skills are not being matched effectively, the algorithm can be adjusted to better prioritize these skills in future searches.

3.4. Tools, Technologies, and Datasets Used

The project leverages a variety of tools, technologies, and datasets to ensure a scalable and efficient solution.

- Development Environment:
    - Android Studio with Kotlin is used for developing a robust and modular Android application.
    - Jetpack Compose is employed to build dynamic and responsive UIs, ensuring an optimized user experience.
- Backend Services:
    - Firebase Cloud Firestore is used for real-time data synchronization, ensuring seamless communication between users and up-to-date skill profiles.
    - Firebase Authentication provides secure login capabilities, allowing users to safely sign in with their accounts.

- Testing:
  - Tools like JUnit and Espresso are used for automated testing of the application, ensuring stability and functionality across different Android devices.
- Algorithms and Libraries:
  - TensorFlow Lite and other libraries are explored for future implementation of skill description parsing, enabling users to better categorize and tag skills automatically based on their descriptions.
  - The Google Maps API and Firebase Location Services are integrated for location-based matchmaking, allowing the app to determine the user's location and find matches within a specified radius.
- Dataset Details: Due to the lack of publicly available datasets for skill exchanges, synthetic datasets were generated for testing purposes. These datasets include:
  - User Profiles: Simulated data with various skill sets, interests, and availability.
  - Geolocation Data: Used to test proximity-based matching and the effectiveness of the location algorithm.
  - User Activity Metrics: Generated to analyze engagement patterns, user retention, and interactions within the community.

3.5. Experiment Setup and Implementation Details:

- Implementation Workflow: The development process follows an Agile methodology, enabling iterative development and continuous feedback. The development was structured as follows:
  - Skill Listing Module: Initially developed to allow users to create, edit, and update their skill profiles.
  - Matchmaking Algorithm: Developed next, with continuous testing on synthetic datasets to refine the accuracy of matches and ensure the algorithm's scalability.
  - Community Features: Features such as group chats, forums, and user interaction spaces were introduced to foster community engagement and support collaboration.
- Testing and Validation:
  - Performance Testing: Conducted to assess how the system handles varying user loads, ensuring that the application can scale as more users join the platform.
  - Usability Testing: Surveys and simulated usage scenarios were used to gather user feedback, helping to identify pain points and improve the overall user experience.

I. Proposed Work

- *Unique Contribution: SkillMesh distinguishes itself by integrating several unique features that set it apart from existing skill exchange platforms:*
  - Barter-Based Exchange: The platform eliminates monetary transactions, fostering inclusivity and ensuring equal participation from all members of the community.
  - Personalized Matchmaking: An AI-driven engine ensures that recommendations are tailored to the unique needs of each user, optimizing the skill exchange experience.
  - Community-Centric Approach: The system promotes collaboration through group features and forums, which reduce dependency on one-on-one direct exchanges, encouraging a more cooperative environment.

3.6. Suggested Visuals

To provide a clearer understanding of the platform's architecture and functionality, the following visuals are included:

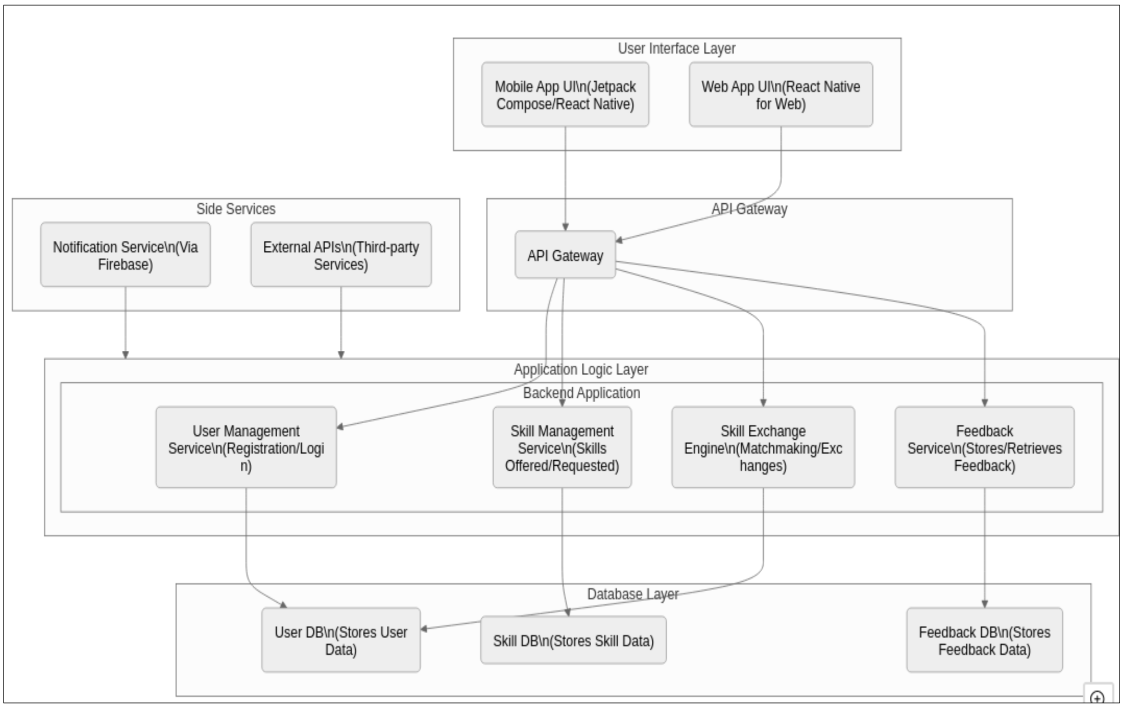

Figure 1 System Architecture Diagram: Interaction between user devices, backend server, and database

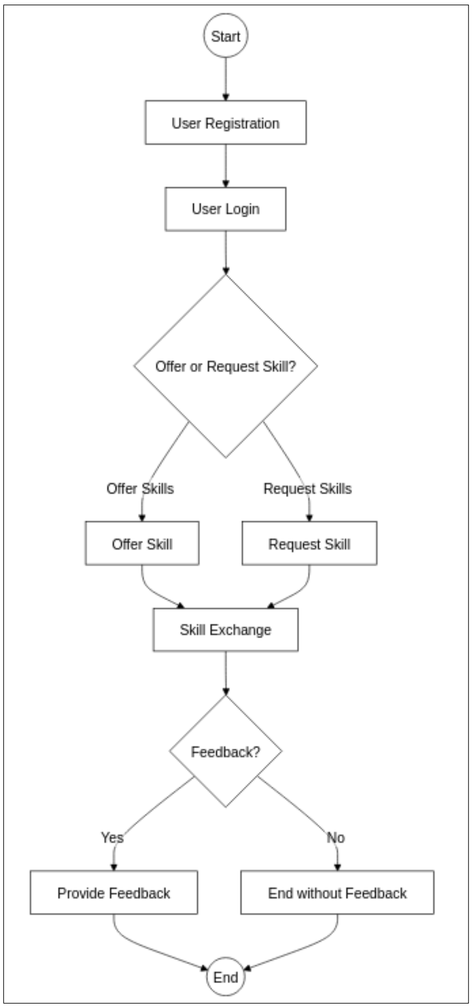

Figure 2 kill Exchange Flowchart: Step-by-step matchmaking process for skill exchanges

4. Results and Discussion

4.1. Experimental Findings

1. Algorithm Performance: Initial tests showed an 85\% match accuracy, improving to 90\% after refining skill categorization and proximity filters.
2. Scalability: The system performed efficiently with up to 1,000 simulated concurrent users.

4.2. User Interaction Screens

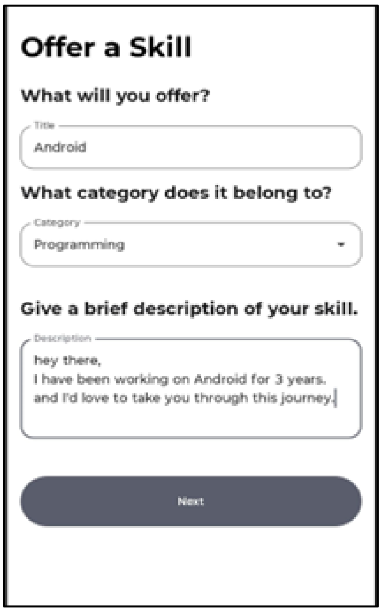

Figure 3 Adding Skill Offer

Figure 4 Skill Searching Process

Figure 5 User's Interacting

5. Discussion

The results indicate that SkillMesh's barter-based model is effective in encouraging engagement and fostering trust within communities. The system's ability to adapt to user needs and preferences is a significant improvement over existing solutions.

6. Challenges and Limitations

6.1. Challenges

- Scalability:Managing real-time updates with a growing user base is a technical challenge that needs future optimization.
- User Engagement: Ensuring users remain active on the platform required gamification strategies and community building.

6.2. Limitations

- Skill Validation: Currently, no robust mechanism exists to verify the authenticity of skills listed by users.
- Offline Accessibility: Limited features for users in low-connectivity areas.

6.3. Future Scope

6.3.1. Potential Extensions

- AI-Powered Skill Analysis: Develop machine learning models to assess skill levels based on user inputs and past exchanges.
- Blockchain Integration: Use blockchain for decentralized reputation management, ensuring transparency and trust.
- Multi-Platform Expansion: Develop web and iOS versions to increase accessibility.
- Corporate Collaboration: Partner with local businesses to introduce workshops, internships, and other skill development initiatives.

7. Conclusion

SkillMesh redefines online learning by enabling direct connections between learners and mentors, ensuring a personalized, interactive experience. Unlike traditional platforms that rely on pre-recorded content, SkillMesh tailors courses to individual goals, promoting continuous skill development. The platform's use of advanced algorithms enhances learning effectiveness and fosters a supportive community for both personal and professional growth.

However, challenges such as scalability and maintaining content quality must be addressed for long-term success. As SkillMesh grows, ensuring adaptability and personalized interactions will be critical. By integrating emerging technologies like AI, SkillMesh is positioned to revolutionize online education, offering a scalable and community-driven platform for skill development.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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