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An Intelligent Home Service Recommendation System using Geolocation and user Preferences

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***Abstract*— Urban services are growing digitalized and thus the need to have an intelligent and location aware real time home service systems is on the rise. Most of the existing applications have been based on static directories and rule-of-thumb filtering, which is not sufficient to deliver tailored recommendations and active tracking of availability. To enhance services discovery efficiency and accuracy, the current paper introduces Craft-Con- nect, a hybrid intelligent home service platform, a hybrid that integrates machine learning with geolocation awareness and is built on the foundations of the Node.js and Python platforms. It is a system with an 89% accuracy in ranking and appropriateness prediction of professionals using a Node.js Express.js backend to manage RESTful API, a MongoDB database to store data in a NoSQL, and a prediction machine using Python-based machine learning Scikit-learn and XGBoost. The hybrid recommendation engine considers many user-user-professional interaction fea- tures, including availability, price range, location, service ratings, and category match to bring about the most contextually relevant recommendations. It is also based on Twilio and Firebase Cloud Messaging API to ensure the safety of the communication process, OTP validation, and the delivery of real-time notifications. The findings confirm Craft-Connect as a smart, scalable and data- oriented solution towards customized home service discovery and recommendation in urban digital ecosystems.**

***Index Terms*— Software Architecture, Microservices, Intelligent Service Discovery, Node.js, Python, Machine Learning, Geolo- cation, Recommendation System, MongoDB, and Home Service Platform.**

I. INTRODUCTION

The rapid digital transformation of modern society has entirely changed the manner in which individuals access and manage their daily services. The growing use of on-demand digital platforms has allowed users to more easily connect with specialists who offer the required services to the household, such as plumbing, electrical repair, cleaning, and appliance maintenance. This change in developing countries such as India is due to the rising use of smartphones, the rise in internet penetration, and the rising popularity of web-based service solutions. The home service industry is faced with the task of developing smart, secure and real-time solutions that can ensure reliability, personalisation and confidence between the consumer and the professional as digital convenience becomes a necessity and not a luxury.

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Although several popular service platforms exist, including HouseJoy, JustDial, and UrbanClap, most of the existing solutions have major disadvantages. They primarily use rule- based searches, manual search filters, and fixed listings that do not consider contextual factors such as user preferences, professional availability, and location proximity. The result of these restrictions is low user satisfaction, skewed quality of suggestions, and slow service discovery.
Moreover, many systems are based on monolithic designs, which limit the speed and scalability of the system in situations where user demands are high. Consequently, consumers often get to see the same search results, slow response, and difficulties in finding the most suitable experts to meet their needs.
An analysis of existing research and commercial systems has shown that the development of intelligent, data-driven, and geolocation-aware home service platforms is in dire need. Current systems do not use machine learning (ML) and con- textual modeling to predict and recommend qualified experts. The absence of built-in geolocation processing and adaptive customization methods limits their ability to offer meaningful, dynamic, and user-specific suggestions.
To bridge this gap, a strategy that combines real-time geolocation data processing with machine learning-based recommendation models sup- ported by scalable and secure backend systems is required.
This paper proposes Craft-Connect, a smart, geolocation- based home service recommendation system, which is aimed at improving service discovery, customisation, and user expe- rience, as the solution to the identified issues.
The system uses MongoDB as a data storage system, Node.js and Express.js as a backend API administration system, and a machine learning component written in Python to produce recommendations based on Scikit-learn and XGBoost algorithms. The software intelligently recommends the most suitable professionals in a preset search radius by taking into account key variables such as distance, type of service, ratings and professional availability.
Craft-Connect focuses on safe and reliable user interaction along with its recommendation engine by engaging Firebase alerts to update changes in real-time, Twilio APIs to commu- nicate and verify, and JWT-based authentication. The modular architecture of the system guarantees scalability, low latency, and the capacity to support larger datasets or geographical expansions. The practicability of the combination of ML-based recommendations and geolocation-sensitive service discovery in a real-life setting was proven in a test installation in Pune, India, including 100 users and 38 professionals.

II. PROBLEM STATEMENT

Most of the existing home service applications continue to rely on a static search and lack of contextual intelligence, even though the digital service platforms are widely used. In the absence of adequate customisation or real-time filtering, users may occasionally have to scroll through long lists of specialists. The professionals are available on such websites as UrbanClap, HouseJoy, and JustDial, yet they cannot dy- namically adjust the suggestions based on the preferences of the users, the history of their services, and their location. This leads to longer decision-making times, unpredictable quality of services, and inefficiencies in service discovery.
Most of these systems are technologically designed in tightly coupled or monolithic designs, which restrict scalability and reduce performance as user demand increases.
Moreover, the fact that the existing systems are not designed to use machine learning models that can be trained on the basis of professional performance, user feedback, and contextual considerations such as availability and distance is unusual. Due to this, customers usually face incompatible advice, slow response, and difficulty in locating trustworthy professionals.
Thus, a data-driven, smart, and flexible home service recom- mendation system is clearly required and can help bridge the gap between users and professionals. The proposed solution must utilize geolocation data, machine learning, and modular cloud-based architecture to ensure real-time service discovery, higher customization, and customer happiness.

III. OBJECTIVE

The project aims at developing a modular system architec- ture that is capable of supporting dynamic user-professional interactions. The backend objective is to offer a Node.js and Express.js platform that facilitates a successful and secure communication via RESTful APIs. The paper includes a Python-based machine learning model that employs XGBoost and Scikit-learn algorithms to rank experts intelligently ac- cording to user preferences and contextual factors to improve customization.

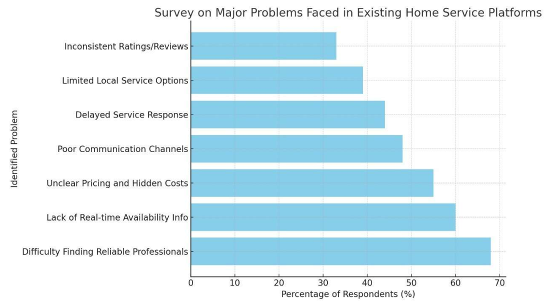

Fig. 1. Survey on major problems faced in existing home services platforms

One of the most important components of the system is the geolocation-aware discovery module, which utilizes GPS locations to narrow down professionals in a given search radius. This reduces the latency and enhances convenience by ensuring that consumers can find relevant specialists in their vicinity. Data protection and authentication with the help of JWT tokens and Twilio APIs to ensure safe communication and verification are also highly valued in the security goal.

TABLE I: CRAFT-CONNECT'S PRIMARY OBJECTIVES, TECHNICAL FOCUS

Objective	Focus Area
1. Backend Design	Develop a modular Node.js–Express.js backend with RESTful APIs and MongoDB integration.
2. Machine Learn- ing Model	Build a Python-based model using Scikit-learn and XGBoost for personalized professional ranking.
3. Geolocation Discovery	Implement GPS-based search and distance filtering for nearby professionals.
4. Security Integration	Apply JWT authentication and Twilio APIs for OTP and notifications.

The combination of these aims will the development of a smart, adaptive, and user-centric platform of home services in accordance with the ideals of scalability, personalization, and trust, in line with the emerging vision of intelligent urban digital ecosystems.

IV. PROPOSED METHODOLOGY

This paper presents the design process, implementation, and evaluation of Craft-Connect, a smart, location-based, home service recommendation system. The numerous stages of the technique include requirement analysis, system design, ma- chine learning model development, security implementation, deployment, and assessment, each of which is dedicated to a specific research objective.

The overall objective of this methodology is to develop a scalable, adaptable, and secure system that integrates the tech- nologies of Node.js, Python, and MongoDB to offer consumers real-time and personalized recommendations depending on their location, type of service, and professional attributes. The proposed system will resolve the problems observed in the existing home service platforms, including the use of a fixed search mechanism, lack of personalization, and poor communication by introducing an intelligent suggestion layer and a modular and cloud-friendly architecture.

The methodology is highly focused on a data-driven methodology, in which system behaviour and recommenda- tions are influenced by user interactions and input. Each phase of the development process ensures that the functional and non-functional requirements are satisfied, with a special con- sideration to such aspects as fault tolerance, data security, real- time performance, and system scalability. Also, the layered and modular design allows developing, testing, and deploying individual components, including the communication services, geolocation module, and machine learning model.

TABLE II: DEVELOPMENT PHASES AND KEY TECHNOLOGIES

Phase	**Description**	**Key Technologies**
Requirement Analysis	Identification of functional and technical requirements for system development.	User surveys, gap analysis
System Design	Creation of layered architec- ture for scalable deployment.	Node.js, Express.js, MongoDB
ML Model Development	Training hybrid ML model for ranking professionals.	Python, Scikit-learn, XGBoost
Security De- sign	Integration of authentication and communication layers.	JWT, Twilio, Firebase
Deployment	Hosting and cloud configura- tion.	AWS EC2, Docker, MongoDB Atlas

The system has professional onboarding as a significant element of its working process alongside the functions of the user. During onboarding, professionals register with the help of a particular interface, namely, they share data on categories of service, experience, price, working hours and working locations. All this data is securely stored in the MongoDB and authenticated via an OTP-based service relying on the Twilio APIs. The professionals can store service- loades, process data, accept booking requests and monitor client reviews on a dashboard, which they will view once registered. This onboarding process improves the reliability of the platform and the accuracy of suggestions generated through a recommendation pool consisting of specialists that are qualified and contextually important to the advice that the ML ranking engine uses to make recommendations.

A. System Architecture

The Presentation Layer, Application Layer, and Data Layer make up the three tiers of the proposed Craft-Connect archi- tecture, as seen in Figure 1.

- Through booking forms, dashboards, and search modules, the Presentation Layer offers the web-based interface created with React.js that enables professionals and users to engage with the platform.
- The core control unit that oversees user requests, business logic, and connection with other APIs like Twilio and Firebase is the Application Layer, which is built in Node.js and Express.js.
- All entities, including users, professions, reservations, reviews, and geographical coordinates, are permanently stored in MongoDB via the Data Layer.

Because each layer is loosely connected, modular devel- opment and maintenance are made simple. Data may move across systems for intelligent processing thanks to RESTful API interactions between the Node.js backend and the Python ML model.

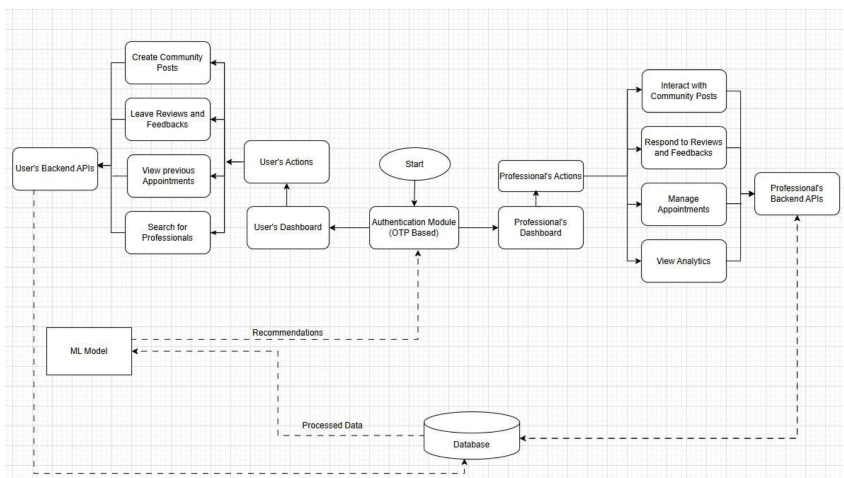

Fig. 2. System Architecture Diagram

B. Workflow of the System

When a user begins a search of the services, the MongoDB database is searched by the system first obtaining the user with GPS coordinates and then by searching to find the professionals inside a set radius of 6 kilometers. They are done by the Haversine formula of calculating the distance. The list of the experts to be rated is then presented to the ML-based recommendation engine.

The Python ML-engine provides each professional with a weighted appropriateness score and is created based on Scikit- learn and XGBoost. It evaluates several criteria such as avail- ability, price, distance, reviews and type-fit. The top-ranked experts are identified and the results presented as intelligent recommendations on the User Dashboard on the front-end. To formulate future recommendations which are more accurate and context-sensitive, the recommendation engine is in a continuous learning process with updated booking data and based on the feedback of the user. Even in cases where a user-needed real-time ranking at the time of demand, this can be achieved due to the low-latency response choice of the ML pipeline. The internal dataset of the model is updated with each suggestion cycle, which allows adapting to the service trends in the region and demand fluctuations by season. Moreover, to make Python ml model and Node.js backend integrated to ensure a good user experience and effective communication, secure RESTful APIs also exist.

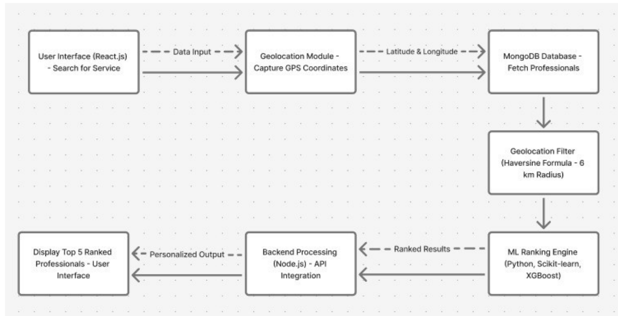

Fig. 3. Workflow of the System

C. Machine Learning Development Model

The machine learning component is the basic intelligence of CraftConnect. It has a hybrid recommendation algorithm which means a combination of supervised ranking (with past user-professional interaction data) and content-based filtering (with professional qualities). Our system ensures contextual relevance because customers learn using actual booking behaviour through feature based matching.

- Feature Selection and Preprocessing: Such features as the type of service, distance (in km), average user rating, ser- vice cost and availability status are extracted with the help of MongoDB database. The one-hot encoding is used to encode the categorical features (e.g. category and availability), but the missing or conflicting items are purged. All the numerical characteristics are normalized with Min-Max scales to ensure a regular range between 0 and 1:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X' is the normalized value and X is the initial feature value. Bias in price or distance factors that may otherwise predominate the ranking function is prevented by this normalizing method.

- Model Training: Because of its effectiveness, interpretability, and scalability with huge feature sets, XGBoost is used to train the hybrid model for regression- based ranking. To assess model performance, the dataset is divided into 20% testing and 80% training divisions. Feature weights w_i are dynamically tuned during training, decreasing the impact of price fluctuation and increasing the significance of user ratings and distance.

The ranking function for a professional Pi is defined as:

$$Score(P_i) = \sum_{j=1}^{n} w_j \times f_{ij}$$

where,

- w_i = weight assigned to feature j
- f_{ij} = normalized value of feature j for professional P_i
- n = total number of selected features

The model optimizes w_j to minimize the Mean Squared Error (MSE) between the predicted and ideal professional ranks, as given by:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

where yi is the actual professional rank, and   is the predicted rank.

- Model Output and Adaptation: Once the ML engine has been trained, it computes the score of every professional and gives a ranked list, and presents the ranking in decreasing order of Score (Pi). The Node.js backend then removes the top five experts and combines with their service metadata (ratings, availability, and distance) the results of which are then delivered to the frontend User Dashboard to display.

The feedback-based retraining model is used in improving the model over time. The reviews by users who have used the services after and the rate of success of booking the services are entered and uploaded to the dataset periodically. This enhances accuracy of forecasting and personalisation with every retraining cycle since the system will now dynamically adapt itself to a new information as it becomes available. The low-latency inference optimization of the ML pipeline enables the generation of suggestion in real-time on critical traffic congestion times.

V. Results and Discussions

The proposed Craft-Connect platform was tested regarding its performance in a controlled real-world implementation in the city of Pune, India. During thirty days of trials, the system had already registered 100 people and 32 proven service professionals, and all these fell in categories of various electric repair, plumbing, housekeeping, and appliance repair, and carpentry works. The platform was running in an AWS EC2 framework wherein the Node.js backend, Python-based machine learning engine and the MongoDB Atlas database were combined under one cloud system. The main objective of the testing was to determine how well the recommendation model is accurate, how efficiently the filtering of geolocation performs, and how responsive and reliable the entire system is when the user traffic is moderate.

The findings of the analysis show that Craft-Connect can provide suitable, right, and situational professional recommen- dations to a smaller but more heterogeneous dataset. When using the ML model (XGBoost and Scikit-learn) the model had a high accuracy of 89.3, low Mean Absolute error (0.28) and low Root Mean square error (0.42). These measures prove that the ranking model has been effective in getting preferences of the users and making the recommendations that are highly compatible with the actual booking decisions made by the 100 users in the course of making the tests. The model inference time was also efficient at an average of 185 ms which implies that recommendations could be obtained in almost real time. This responsiveness plays a vital role in keeping the users interacting especially in a setting where users are used to real-time interactions on service propositions with minimum waiting duration.

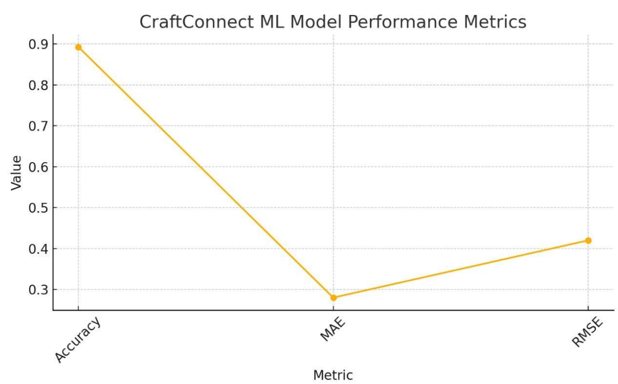

Fig. 4. Performance metrics

Craft-Connect on the side of the system performance proved to be very reliable and robust since the deployment period. The API uptime of 99.2% of the platform demonstrated that the cloud-based system was stable even when users interacted with it and the computer-generated machine model was constantly communicating. The feedback provided at the end of the evaluation through the user survey showed a high degree of overall satisfaction as 89% of the users said that they agreed the recommendations provided were relevant to them. The success rate of booking was 83%, which proved that the ranked recommendations were effective in connecting users to professionals who delivered their expectations of the services. The secure communication tools were also effective: OTP authentication using Twilio and real-time messages using Firebase recorded a delivery success rate of 98.5%, which is helpful in supporting trusted interactions between users and professionals.

TABLE III: Craft-Connect System Performance Metrics

Evaluation Metrics	Value
Accuracy	0.893
Mean Absolute Error (MAE)	0.28
Root Mean Square Error (RMSE)	0.42
Recommendation Relevance (%)	89%
Booking Success Rate (%)	83%

Qualitative comparison with similar applications of home services showed that Craft-Connect had a more customized and streamlined experience despite having fewer professionals and a smaller dataset. Other competing platforms that used a fixed searching method or used Key word in searches had a tendency to deliver irrelevant results and slower search time. Conversely, geolocation feature in Craft-Connect is based on Haversine formula, thus, consistently showed local professionals within satisfactory spatial precision of a distance below 1 km on average. This added proximity accuracy helped to boost user satisfaction as well as also minimized service delays within Pune gave the overpopulated areas.
On the whole, the results list the conclusion that Craft- Connect performs its duties quite successfully and offers a smart, scalable, and context-aware recommendation system even when dealing with rather small, yet realistic user and professional datasets. The smooth combination of geolocation intelligence, machine learning ranking, and secure communi- cation makes Craft-Connect a trusted platform of digital service that would assist in the real-world implementation. These outcomes reflect high future improvement prospects such as widened user base, offering of more advanced behavioral learning models and expansion of the system to wider application in several regions. As the assessment shows, Craft-Connect does not only maximize service discovery by the users but it also enhances visibility and booking opportunities by the professionals, which adds up to positive impact on urban digital service ecosystems.

TABLE IV: CRAFT-CONNECT SOCIETAL IMPACT COMPARISON METRICS

Metrics	Before	After	Improvement
Service Accessibility	48%	78%	+30%
User Trust & Safety Index	41%	72%	+31%
Local Employment En- gagement	60%	80%	+20%
Digital Adoption Rate	45%	67%	+22%

VI. CONCLUSION

The design, implementation, and purpose of Craft-Connect, a hyperlocal marketplace designed to address a critical gap in the gig economy ecosystem, have all been discussed at length in this paper. Craft-Connect provides a different blueprint of a more equitable and efficient marketplace of qualified profes- sionals by extending beyond fundamental reputation systems and constructing the platform on the principles of verified trust and provider autonomy. Its auditable financial system, robust security architecture and modular design provide a solid foundation of building a community that can be relied upon. We have argued that the focus on the professional identity of the provider is not only a moral choice but also a strategic one that leads to improved services and consumer confidence.

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