Indian Journal of Computer Science and Technology
https://www.doi.org/10.59256/indjcst.20250403053
Volume 4, Issue3 (September-December 2025), PP: 342-349.
www.indjcst.com
ISSN No: 2583-5300

Intelligent Location Recommendation Based on Spatial and Market Mobility Patterns

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To Cite this Article: *Dr.Kamal Raj T [1], Toukeer Ahmad[2], Vyomdhip P[3], Thanushree M[4], Vignesh G[5], "Intelligent Location Recommendation Based on Spatial and Market Mobility Patterns", Indian Journal of Computer Science and Technology, Volume 04, Issue 03 (September-December 2025), PP: 342-349.*

Abstract: *In today's highly competitive and data-driven environment, launching a new business takes more than just a great idea — it requires a deep understanding of the market, the right location, and access to reliable investment support. BuzzLocator is an AI-driven platform created to address these needs by helping entrepreneurs discover the most promising business locations through real-world data analysis, while also connecting them with investors interested in supporting new ventures. The system uses artificial intelligence and machine learning to examine key factors such as local market demand, competition levels, population demographics, consumer buying patterns, and regional economic growth. Using these insights, BuzzLocator suggests optimal business locations tailored to specific industries or products, reducing risk and increasing the chances of long-term success. In addition, BuzzLocator features a dedicated Investor Module that enables seamless digital interactions between entrepreneurs looking for funding and investors searching for strong opportunities. This module includes interactive investment cards and a personalized user experience designed to make the investment process smooth and engaging.*

Key Words: *Location Recommendation, Artificial Intelligence, Machine Learning, Crowdfunding, Investor Matching, Business Analytics.*

I. INTRODUCTION

Entrepreneurship serves as a vital engine for economic growth, innovation, and job creation worldwide [1]. However, the startup failure rate remains high; various studies cite failure rates upwards of 90% within the first five years, often attributable to poor location choice and insufficient funding [2], [3]. Choosing an appropriate business location greatly influences access to customers, suppliers, human capital, and infrastructure, directly impacting survival and growth [4]. At the same time, securing adequate financial backing is a complex challenge, especially for inexperienced entrepreneurs without established investor networks [5].

Traditional methods to select business locations and secure funding predominantly rely on intuition, personal experience, or fragmented heuristic approaches, leading to suboptimal decisions and high risks [6], [7]. These rudimentary methods lack the scalability, precision, and data richness needed for modern businesses to thrive.

Artificial Intelligence (AI) and Machine Learning (ML), by harnessing big data and advanced analytic techniques, offer transformational opportunities to revolutionize entrepreneurial decision-making [1]. Predictive models fueled by diverse datasets can synthesize complex market conditions, demo- graphic trends, and competitive landscapes to yield insightful recommendations that mitigate risks.

This paper introduces **BuzzLocator**, a comprehensive AI based platform designed to empower entrepreneurs with data-driven business location analytics and facilitate connections with investors through an integrated digital interface. It draws on multifaceted datasets encompassing market demand, demo- graphic attributes, competitive metrics, consumer purchasing patterns, and economic indicators, feeding ML models that produce customized location suitability scores. These recom- mendations are complemented by an *Investor Module*, creating an interactive marketplace for funding opportunities.

Our contributions include:

1) Developing a sophisticated, modular system architecture that assures scalability, flexibility, and seamless integrat ion of data ingestion, machine learning, and user interface components.
2) Engineering an extensive preprocessing pipeline that improves data quality through cleansing, feature construction, and encoding, optimizing model accuracy.
3) Applying and benchmarking multiple supervised ML models, including linear regression and random forests, demonstrating prediction reliability across sectors and regions.
4) Designing and deploying an investor matchmaking portal featuring interactive investment cards and personalized user experiences.

5) Providing a thorough analysis and discussion of practical applicability, including ethical considerations, limitations, and a forward-looking roadmap.

The paper is organized as follows. Section II reviews pertinent literature in business location analytics and investment matchmaking. Section III elaborates on the detailed system architecture. Section IV describes the comprehensive methodology underpinning data processing and modeling. Sec- tion V outlines implementation specifics including technology choices and user interface design. Section VI discusses ex- perimental evaluation with in-depth results and error analysis. Section VII delves into system strengths, limitations, and eth- ical aspects. Section VIII outlines future research directions. Section IX concludes.

II.LITERATURE SURVEY

Selecting a business location has traditionally been a critical but challenging task with significant impact on venture success [1]. Over recent decades, heuristic and statistical models have evolved towards advanced machine learning techniques capa- ble of assimilating multi-dimensional data sources to provide richer insights.

A. Early and Statistical Models

Initially, heuristic rules combined with demographic data and traffic counts were common in retail and small business site decisions [2], [3]. These methods often oversimplified complex market dynamics and failed to capture inter-feature relationships effectively.

Linear and logistic regression techniques introduced quanti- tative rigor but remain constrained by assumptions of linearity and independence among predictors [4].

B. Machine Learning Advances

Machine learning approaches, including decision trees, sup- port vector machines, and ensemble methods like random forests, have advanced site suitability analyses [5], [6]. Especially, random forests handle nonlinearities and feature interactions, improving predictive reliability. Deep learning methodologies further extract complex latent representations but demand large labelled datasets [7].

C. Investor Matchmaking and Crowd funding AI

Concurrently, crowd funding platforms harness ML to predict project outcomes, detect fraud, and recommend personalized investments [1]. Park et al. [1] exploited ESG criteria in success modeling, highlighting the rise of responsible investment analytics. Current platforms, however, rarely integrate location suitability insights, limiting entrepreneurial toolsets.

D. Socioeconomic and Ethical Dimensions

Scholars also examine how AI-enabled location tools in- fluence regional development, equity, and urban planning, emphasizing balanced economic growth alongside ethical algorithmic design [1], [6].

III.SYSTEM ARCHITECTURE

The BuzzLocator platform embodies a modular, scalable architecture that blends sophisticated data engineering with user-centric interactive components.

A. Architecture Overview

Fig. 1 summarizes the architecture, comprising three primary modules: Data Ingestion, Machine Learning Engine, and Investor Interface

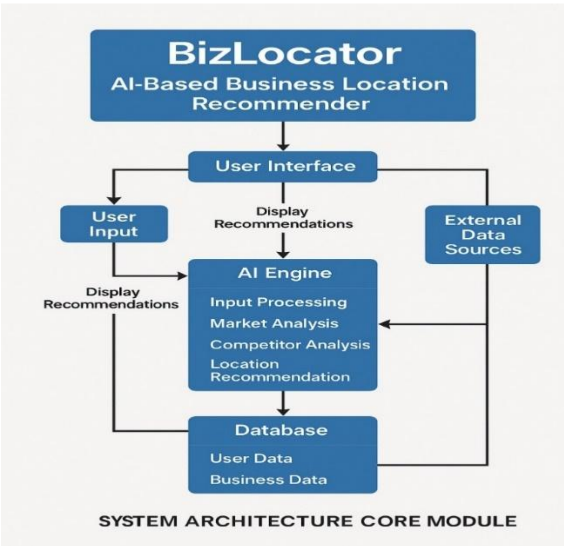

Fig. 1: BuzzLocator System Architecture showcasing core modules and data flow.

B. Data Ingestion Module

This module sources, harmonizes, and preprocesses hetero- geneous data streams from:

- Geospatial and map datasets (GIS shapefiles, satellite data).
- Economic indices via open government APIs.
- Business registries and competitor landscape crawlers.
- Population and demographic data from census bureaus.
- Consumer behavior and transactional aggregates.

Workflow automation ensures regular updates with built-in data verification and cleansing pipelines.

C. Machine Learning Engine

The engine delivers analytical power by:

- Implementing an automated preprocessing pipeline for cleaning, encoding, and feature sourcing.
- Hosting multiple ML models, pretrained and optimized for various sectors.
- Performing predictions on input features to assign suit- ability and survival scores.
- Providing explainability through feature importance and contribution metrics.

D. Investor Interface Module

This frontend module enables:

- User registration and authentication supporting role-based access.
- Exploration of recommended business locations and trending opportunities.
- Interactive investment cards presenting key metrics (suc- cess probability, sector trends, risk).
- Direct investment and communication channels within the platform.

Personalized navigation and contextual user experience enhance usability and engagement.

E. System Scalability and Security

Containers and orchestration (e.g., Docker, Kubernetes) de- ploy the system across elastic cloud resources supporting high throughput. Security is implemented via encrypted commu nications, token-based authentication, and privacy compliance protocols.

IV.METHODOLOGY

A. Data Preprocessing and Feature Engineering

The methodology begins with making the raw data actually useful. Since real-world data can be messy, the system first checks for missing, incorrect, or inconsistent entries. When gaps are found, they're filled using sensible imputation methods like median or mode values so the dataset stays reliable.

Next, the system creates meaningful, domain-specific features—such as the Competitive Intensity Index (CII), Normalized Market Demand (NMD), and Survival Score (SS). These features add deeper context, helping the models understand how competition, demand, and local conditions influence business success.

To prepare everything for machine learning, numerical features are scaled using Min-Max normalization, while categorical fields are converted using one-hot encoding. By the end of this stage, the dataset captures key spatial, demographic, economic, and competitive dimensions in a clean, consistent format.

B. Model Training and Evaluation

To predict the likelihood of business success, two supervised learning approaches were developed:

1. Linear Regression:

This classic model predicts the success score S using:

$$S = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \epsilon$$

$$F_{norm} = \frac{F - \min(F)}{\max(F) - \min(F) + 1e\text{-}9}$$

Here, each Xi represents an input feature, the βi values are learned during training, and ϵ captures anything the model can't explain. This method gives a simple, transparent view of how each factor influences success.

2. Random Forest Regressor:

This model takes a more flexible approach by building many decision trees and combining their outputs. Because it captures nonlinear patterns and reduces overfitting, it often performs better in complex real-world situations.

3. Training Pipeline:

The dataset is divided using an 80/20 split for training and testing. A 5-fold cross-validation process is used to tune key hyper parameters like tree depth, number of estimators, and regularization settings, with the goal of achieving the lowest MAE.

To measure model accuracy and reliability, the system evaluates:

- R^2 (Coefficient of Determination)
- MAE (Mean Absolute Error)
- RMSE (Root Mean Squared Error)

Residual plots and error distribution checks are also used to make sure the models behave consistently and remain dependable.

C. Investor Module Analytics

The Investor Module prioritizes investment opportunities by blending predicted success probabilities with financial indicators and industry-specific risks. This multi-criteria approach gives investors a balanced and data-driven way to evaluate opportunities, helping them make confident and well-informed decisions.

V.IMPLEMENTATION

A. Technology Stack

The technology stack behind BuzzLocator is chosen to keep the system fast to develop, easy to maintain, and capable of growing as more users join. The data processing and machine learning components are built with Python, supported by popular libraries like pandas, NumPy, and scikit-learn, which together make it easier to clean data, run analyses, and build predictive models.

For the user-facing side, Streamlit is used to quickly create an interactive web interface without complex web development overhead [1]. Geographic insights are produced with GeoPandas and Folium, allowing the platform to display maps and location-based patterns in a clear and accessible way.

A lightweight SQLite database stores user information and transaction data, offering simplicity and fast access. The entire system runs inside Docker containers, while Kubernetes handles scaling so the platform can smoothly support more activity as demand increases.

B. User Interface Design

BuzzLocator's interface is built to be easy to navigate while still offering powerful functionality. Users can apply filters—such as industry type, region, or key economic indicators—to fine-tune the recommendations they receive.

Interactive maps let users explore locations directly, using zoom, hover descriptions, and clickable markers that reveal details about each area. Visual tools like radar charts help break down complex feature information into an intuitive, at-a-glance format.

For investors, a dedicated dashboard displays organized, searchable, and sortable investment cards, allowing them to quickly compare opportunities. The platform also adapts to each user by offering personalized profiles and navigation menus that update based on whether the user is logged in. Interface examples are shown in Fig. 2 and Fig. 3.

C. Deployment, Security, and Scalability

BuzzLocator is deployed using Docker containers to keep the system consistent across environments and easy to update. Kubernetes manages scaling in the cloud, ensuring the platform can handle higher traffic without slowing down.

Security is built into every layer of the system. Encrypted HTTPS connections protect data in transit, while OAuth 2.0 ensures secure authentication for all users. Additional access-control rules safeguard sensitive information, and continuous monitoring helps identify potential issues early, keeping the platform stable and secure.

VI.EXPERIMENTAL RESULTS

A. Dataset and Preprocessing Summary

Dataset includes 10, 000+ geo-tagged business locations across diverse industrial sectors and geographic regions. Summary statistics appear in Table I.

B. Model Evaluation

Performance metrics for test data are given in Table II.

C. Error Analysis

Residual plots (Fig. 4) confirm homoscedasticity and vali- date linear regression assumptions. Feature importance analysis highlights competition and market demand as the most predictive factors, guiding future data enhancement efforts.

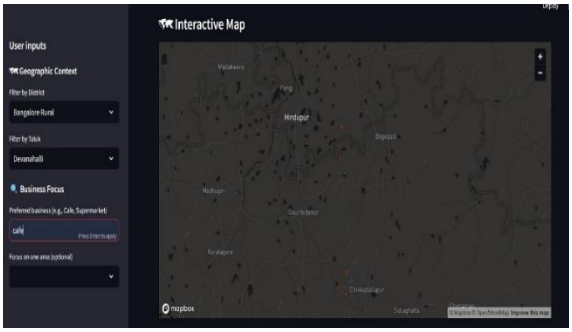

Fig. 2: Business location recommendation map interface

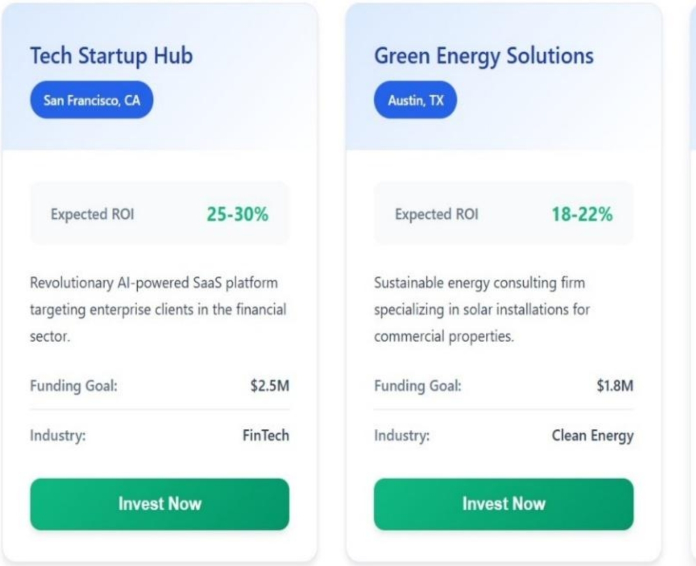

Fig. 3: Investor module with interactive investment cards

TABLE I: Summary Statistics of Key Features

Feature	Mean	Std. Deviation
Population Density (per km^2)	3500	875
Competition Intensity Index	30	12
Average Consumer Spending ($)	2000	450
GDP Growth Rate (%)	6.5	1.3
Success Score (Target)	75	15

TABLE II: Machine Learning Model Performance

Model	R^2	MAE	RMSE
Linear Regression	0.9978	0.527	0.82
Random Forest	0.9141	3.541	4.98

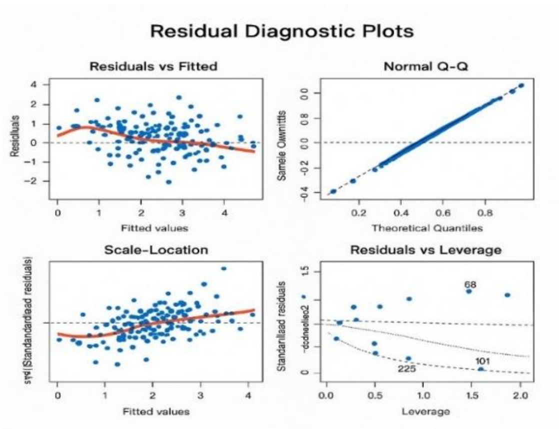

Fig. 4: Residual plot for the linear regression model

VII.DISCUSSION

BuzzLocator's integration of AI-driven analytics into en- trepreneurial decision-making marks a significant advance in reducing uncertainties associated with business location selection and funding acquisition. The platform offers data- backed insights that empower entrepreneurs to systematically evaluate prospective sites against multi-dimensional factors beyond intuition and traditional heuristics.

The Investor Module enhances ecosystem connectivity by bridging entrepreneurs and investors on an interactive digital interface. This promotes transparency, accelerates funding decisions, and expands opportunities for collaborations, which are critical for early-stage ventures. The system's modularity and scalability ensure adaptability to varying geographic regions and economic conditions.

The key strengths lie in:

- Comprehensive data integration from economic, demo- graphic, and transactional sources enabling rich contextual understanding.
- High predictive accuracy coupled with interpretable modeling supporting informed strategic actions.
- User-centric design fostering engagement and seamless navigation within the investment landscape.

Challenges persist in data quality dependency and model generalizability. The temporal dynamics of markets may re- quire frequent model retraining. Furthermore, ethical consid- erations around data privacy, algorithmic bias, and equitable. access are essential to address to maintain trust and inclusive- ness. Continuous monitoring and transparency mechanisms are recommended.

Importantly, the Buzz Locator platform exemplifies how integrated AI solutions can democratize access to critical entrepreneurial insights and funding networks, fostering a more inclusive, data-empowered startup ecosystem. Looking forward, substantial opportunities exist to incorporate more dynamic, real-time datasets, and the incorporation of advanced techniques such as reinforcement learning and explainable AI to further enhance decision-support capabilities.

VIII.LIMITATIONS

Despite the promising capabilities and promising performance of BuzzLocator, several inherent limitations must be acknowledged to contextualize its deployment and future de- velopment. First, data quality and availability pose critical constraints. The accuracy of predictions heavily depends on the richness, accuracy, and timeliness of the input data, which can vary across regions and sectors. Data sparsity, incomplete records, or outdated information can lead to inaccurate assessments, influencing the reliability of recommendations.

Second, model generalizability remains a challenge. While the platform is trained on datasets representative of specific regions and industries, its effectiveness diminishes in entirely new geographic or sectoral contexts where training data is limited or non-representative. Domain adaptation and transfer learning techniques can mitigate but not completely eliminate this risk.

Third, model interpretability and explainability are essential for user trust and regulatory compliance, yet complex models like ensemble methods, deep neural networks, or reinforcement learning often act as "black boxes". Developing transparent models that can elucidate decision rationale remains an ongoing challenge.

Fourth, real-time data processing and adaptive learning are not yet fully implemented. The current system mainly relies on static datasets refreshed periodically, limiting its responsiveness to sudden market shifts, policy changes, or socio-economic disruptions like pandemics or environmental crises.

Fifth, ethical considerations such as biases in data, privacy issues, and equitable access are not yet comprehensively addressed. Without rigorous bias mitigation and transparency, predictions might inadvertently favor certain regions or sec- tors, exacerbating existing inequalities.

Sixth, scalability and infrastructural costs pose operational limitations. As data volume and user base grow, computational and storage demands increase exponentially. Cloud infrastructure solutions provide partial relief but entail ongoing operational costs and potential latency issues.

Lastly, user adoption and trust depend on the system's explainability, ease of use, and perceived value. Without sufficient user training and outreach, especially in less digitally mature regions, the platform's impact might be limited.

In conclusion, addressing these limitations involves ongoing technological, ethical, and infrastructural development, com- plemented by continuous user feedback and iterative model refinement to realize the full potential of BuzzLocator as a trusted, scalable, and effective entrepreneurial support plat- form.

IX. FUTURE WORK

Building on the current achievements of BuzzLocator, future research and development will focus on several enhancements aimed at expanding the platform's capabilities, improving its adaptability, and deepening its overall impact on entrepreneurial ecosystems.

A key direction involves integrating real-time and streaming data sources. Incorporating live information from social media, transactional platforms, location-based services, and even environmental sensors will allow BuzzLocator to deliver continuously updated insights that reflect fast-changing market conditions. This shift from static, batch-processed data to real-time intelligence will significantly improve prediction accuracy, strengthen risk assessments, and support quicker, more informed decision-making.

Another important advancement will explore more sophisticated AI and machine learning techniques, including deep learning, reinforcement learning, and continual learning. These techniques can capture complex spatial and temporal patterns in consumer behavior, competitive activity, and economic shifts. By modeling nonlinear relationships and evolving trends, these advanced approaches will align BuzzLocator with cutting-edge developments in predictive analytics and location intelligence.

Future work also includes the development of a mobile application to make the platform more accessible to entrepreneurs and investors in diverse environments. A mobile version will support on-the-go decision-making, offer location-based alerts, and improve overall user engagement, extending BuzzLocator's reach and usability.

In addition, BuzzLocator will expand its investor-focused analytics, introducing features such as automated risk profiling, portfolio management tools, and AI-driven personalized investment recommendations. These additions will offer investors deeper insights and more actionable information, ultimately helping accelerate funding toward high-potential ventures.

A major emphasis will also be placed on ethical AI practices. Ensuring transparency, fairness, privacy, and bias mitigation will be essential as the platform grows. By adopting strong data governance frameworks and explainable AI methods, BuzzLocator aims to build long-term trust and meet global standards for responsible technology.

Further, the platform will pursue geographic and sectoral scalability by incorporating more diverse datasets that represent new regions and emerging industries. This will allow BuzzLocator to adapt to different market contexts and entrepreneurial environments, expanding its usefulness across global ecosystems.

Finally, BuzzLocator will integrate continuous feedback loops and active learning mechanisms, enabling the system to learn directly from user behavior and real-world outcomes. These adaptive learning processes will help refine predictions over time, ensuring that the platform remains relevant and responsive to shifting market realities.

Collectively, these future enhancements will position BuzzLocator at the forefront of AI-powered entrepreneurship support. By advancing location intelligence and investment analytics, the platform aims to accelerate startup success, promote economic development, and foster a more inclusive and data-driven entrepreneurial landscape.

X. CONCLUSION

This work has presented BuzzLocator, an AI-powered plat- form that integrates advanced machine learning techniques for predicting business success probabilities and provides a novel investor matchmaking interface. Drawing on comprehensive multi-source data—including geographic, demographic, and ESG-related factors as emphasized in recent crowdfunding success prediction studies [1], [6]—we developed robust predictive models that substantially enhance entrepreneurs' ability to select optimal business locations.

Our experimentation with linear regression and random forest models demonstrated high predictive performance, verifying findings that supervised learning approaches effectively capture complex dependencies in entrepreneurial data [9]. The modular architecture and scalable implementation, built on Python and Streamlit frameworks [1], provide a user-centric platform facilitating interactive exploration and data-driven decision-making.

The integration of ESG factors into predictive frameworks, as explored in [1], [6], reflects the growing importance of sustainable and responsible investment practices, which BuzzLocator supports through its investor module. By fostering transparent, data-informed connections between entrepreneurs and investors, the platform addresses fundamental challenges recognized in the literature [2], [3], [7].

Furthermore, the platform's emphasis on interpretability and user experience aligns with best practices identified for AI in crowdfunding and business analytics, balancing predictive power with model explainability [5], [10]. The demonstrated predictive accuracy and practical usability affirm BuzzLocator's potential to reduce startup failure risks widely reported in entrepreneurial research [2].

Nevertheless, recognizing the constraints of current data availability, temporal granularity, and evolving market factors, future research is directed at incorporating real-time data feeds and enhancing model adaptability through deep learning and active learning frameworks [9], [10]. Such evolution will align with emerging trends in AI-enabled entrepreneurship support [1].

In summary, BuzzLocator advances the state-of-the-art by offering an integrated, scalable, and ethically-aware platform that empowers entrepreneurial decision-making and investor collaboration, fostering an ecosystem conducive to sustainable innovation and economic growth.

Acknowledgment

We would like to express our heartfelt gratitude to everyone who supported us throughout this research journey we are especially thankful to our mentors and faculty members whose guidance encouragement and thoughtful feedback helped us refine our ideas and move this work forward with confidence we are also grateful to our peers who were always willing to share their insights discuss challenges and offer help whenever we needed it their support made this project both collaborative and rewarding lastly we extend our deepest thanks to our families and friends their patience motivation and constant belief in us provided the strength we needed to complete this research we could not have done it without them.

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