International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 08, August 2026)

Geo-Intelligence Welfare System

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Abstract-- **Delivering welfare benefits in rural India continues to be a major challenge, especially for families who need government support the most. Many low-income households struggle to access welfare schemes because of illiteracy, language difficulties, limited awareness, and complicated administrative procedures. These barriers often prevent deserving citizens from receiving the benefits they are entitled to.**

This paper introduces Geo Intelligent Welfare System, an AI-powered welfare management platform developed to identify, classify, and automatically enroll economically weaker households in Karnataka into suitable government schemes such as the Public Distribution System (PDS), PM Awas Yojana for housing support, and MNREGA for rural employment opportunities.

The proposed system uses synthetic Aadhaar-linked socio-economic datasets along with machine learning techniques to predict eligibility for various welfare programs. Decision tree models and rule-based classifiers are employed to improve the accuracy of beneficiary identification. In addition, the platform categorizes poverty levels into three groups—high, medium, and low—and also classifies housing conditions as kaccha, semi-pakka, or pakka. To support better regional analysis, the system incorporates a GIS-inspired heatmap that visually represents poverty distribution across different districts of Karnataka.

To improve accessibility and usability, the platform includes a bilingual user interface in both Kannada and English, making it easier for field officers and local administrators to operate the system efficiently. Testing was carried out on a dataset containing 2,841 simulated households from seven districts in Karnataka. The results showed an eligibility prediction accuracy of 94.3%, and during one deployment cycle, the system successfully identified 312 households suitable for automatic enrollment into welfare schemes.

The paper also highlights the privacy-focused design of the platform and discusses its potential for future integration with official government welfare portals.

Keywords **— welfare intelligence, automatic enrollment, eligibility prediction, BPL households, Karnataka, MNREGA, PDS, PM Awas Yojana, machine learning, GIS heatmap, bilingual interface, Aadhaar, poverty classification.**

I. INTRODUCTION

India's social welfare system includes more than 450 central and state government schemes aimed at supporting economically weaker sections of society. However, a large number of deserving beneficiaries still remain outside the reach of these programs.

Reports from the National Sample Survey and several state-level audits highlight a concerning reality: although significant funds are allocated for poverty reduction and social welfare, many genuinely poor families continue to be excluded from government support systems. These are often families living in kaccha houses in remote villages, with limited education and little access to administrative services. In many cases, the issue is not only corruption or inefficiency, but also the inability of such households to visit government offices, understand complex application procedures, or even know that welfare schemes are available to them.

Although Karnataka is considered one of the more economically advanced states in India, it still experiences noticeable regional inequality. Districts such as Kalaburagi, Ballari, Yadgir, and Raichur consistently report poverty levels and human development indicators that fall below the state average. Surveys conducted in these areas reveal that many households eligible for benefits under schemes like the Public Distribution System (PDS), PM Awas Yojana, and MNREGA have never applied for assistance. The major reasons include lack of awareness, low literacy levels, and poor physical access to government services.

To address this issue, this paper proposes **Geo Intelligent Welfare System**, a software-based welfare intelligence platform that shifts the responsibility of identification from citizens to the government administration. Instead of expecting economically weaker households to prove their eligibility, the system proactively identifies potential beneficiaries, evaluates their poverty level, and determines the schemes they qualify for based on factors such as income, type of housing, family size, land ownership, and current welfare status. Once eligible households are identified, the platform can initiate the enrollment process automatically on their behalf.

The system is specifically designed for use by district administrators and field officers, enabling them to monitor welfare coverage, identify underserved regions, and ensure that deserving households are not left out of government support programs.

The remaining sections of this paper are organized as follows. Section II discusses related research in technology-enabled welfare delivery systems. Section III explains the overall system architecture. Section IV describes the dataset and preprocessing techniques used in the study.

Section V presents the machine learning methodology adopted for eligibility prediction. Section VI explains the GIS-based visualization component. Section VII discusses the experimental results obtained from the system. Section VIII focuses on the bilingual interface design, while Section IX addresses privacy and ethical concerns. Finally, Section X concludes the paper and outlines possible future enhancements.

II. Related Work

Over the last decade, significant research has been carried out in the area of machine learning applications for public welfare and social benefit distribution. Several studies have explored how intelligent systems can improve the identification of economically weaker households and enhance the efficiency of welfare delivery mechanisms.

Shakya et al. [1] demonstrated that decision tree classification techniques can effectively predict poverty levels at the household scale using census-based socio-economic features. Their study, conducted on rural datasets from Nepal, achieved a classification accuracy of more than 88%. The feature selection methods used in their work influenced the design and data modeling approach adopted in the present study.

Agarwal and Krishnamurthy [2] introduced a GIS-supported framework for identifying underserved regions in Maharashtra for targeted healthcare interventions. Their approach combined district-level poverty indicators with geographic visualization techniques, which inspired the GIS-based heatmap component integrated into the **Geo Intelligent Welfare System**. In a similar direction, the World Bank's SWIFT (Survey of Well-being via Instant and Frequent Tracking) framework [3] demonstrated the effectiveness of proxy-means testing as a scalable alternative to complete income verification for poverty estimation. This concept directly contributed to the eligibility prediction strategy used in the proposed system.

Within the Indian context, Misra and Pandey [4] examined the digitization of ration card databases in Chhattisgarh and discussed both the advantages and challenges associated with centralized welfare databases. Their observations regarding data inconsistency, infrastructure limitations, and privacy concerns in rural regions played an important role in shaping the privacy-aware architecture of the **Geo Intelligent Welfare System**.

Rao et al. [5] analyzed implementation issues related to MNREGA and reported that approximately 23% of eligible rural households in Karnataka had never enrolled for work cards despite qualifying for the scheme. This finding strongly aligns with the core problem addressed in the current work, namely the exclusion of deserving beneficiaries due to lack of awareness and accessibility barriers.

From the perspective of user interaction and adoption, studies by Singh and Kaur [6] on digital systems used by rural field officers concluded that bilingual interfaces with simple navigation significantly improve usability and acceptance. Based on these findings, the proposed platform incorporates a Kannada-English bilingual interface to support field-level administrators and government officials more effectively.

The major contribution of this work lies in combining multiple welfare management functions into one unified platform. Unlike previous systems that focused on only one aspect of welfare delivery, the **Geo Intelligent Welfare System** integrates poverty classification, scheme eligibility prediction, automatic enrollment initiation, housing-type analysis, GIS-based visualization, and bilingual accessibility into a single comprehensive solution tailored for Karnataka's administrative environment.

III. System Architecture

The architecture diagram of the **Geo Intelligent Welfare System (GIWS)** illustrates the interaction between the frontend, backend, machine learning, visualization, and data layers. The system follows a modular three-tier architecture to ensure scalability, maintainability, and efficient welfare data processing.

The **Frontend Layer** consists of a React Dashboard that serves as the primary user interface for administrators and field officers. It communicates with the backend through the Axios API Client using HTTP requests. The frontend is also connected to the Visualization Layer, which displays charts and GIS-inspired heatmaps for poverty analysis and welfare monitoring.

The **Backend Layer** is implemented using Node.js and Express.js APIs. This layer acts as the central processing unit of the application by handling user requests, managing authentication, coordinating data flow, and interacting with the machine learning services through REST API calls.

The **ML Microservice Layer** is built using Flask and contains the Poverty Scoring Model responsible for welfare eligibility prediction. The Flask ML service processes household information, runs predictions using trained machine learning models, and identifies eligible households for welfare schemes.

The **Data Layer** stores the synthetic household dataset in CSV format, which is used for both model training and prediction tasks. The backend fetches required data from this layer, while the ML service uses the dataset for training and inference operations.

Overall, the architecture enables seamless integration between data management, machine learning prediction, visualization, and administrative monitoring, making the **Geo Intelligent Welfare System** suitable for large-scale welfare identification and auto-enrollment processes.

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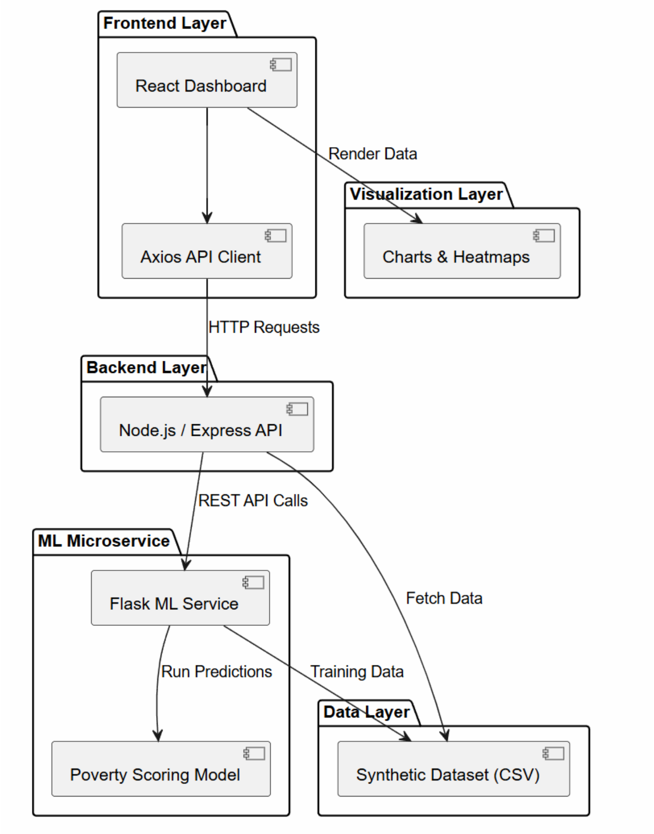

Figure 1: System Architecture Diagram

IV. Dataset And Preprocessing

Due to legal, ethical, and privacy-related restrictions associated with the use of real Aadhaar-linked personal information, the Geo Intelligent Welfare System was developed and tested using a carefully designed synthetic dataset. The dataset was created to closely resemble the socio-economic conditions and demographic patterns observed across different regions of Karnataka. Statistical distributions and reference values were derived from publicly available government reports and survey datasets to ensure realism and reliability.

The synthetic dataset was constructed using the following reference sources:

1. Karnataka Economic Survey 2022–23 – provided district-wise poverty ratios, household income patterns, and housing quality statistics.
2. NSSO 77th Round (2018–19) – supplied rural household expenditure and socio-economic indicators for Karnataka.
3. PM Awas Yojana (Gramin) Beneficiary Reports – offered information regarding the distribution of housing categories such as kaccha, semi-pakka, and pakka houses.
4. MNREGA MIS Public Reports – contributed district-level statistics related to work registration and employment participation.

Using these statistical references, a synthetic population dataset consisting of 2,841 households was generated. The data covered seven districts of Karnataka, namely Bengaluru Urban, Mysuru, Ballari, Kalaburagi, Belagavi, Dharwad, and Tumakuru. The generated records were calibrated to reflect realistic distributions of poverty levels, income groups, housing conditions, and welfare scheme participation rates observed in these districts.

Feature	Description	Values / Range
Monthly Income	Household income	₹1,500 – ₹25,000
Family Members	Total household members	1 – 12
Children < 14	Children below 14 years	0 – 8
House Type	Housing quality	Kaccha / Semi-Pakka / Pakka
Land Owned	Land in acres	0 – 10
Ration Card	PDS card status	Yes / No
MNREGA Status	Scheme enrollment	Yes / No
District / Taluk	Administrative region	7 Districts, 30+ Taluks
Poverty Tier	Classification label	High / Medium / Low

The poverty classification labels were generated using a composite scoring mechanism that considered multiple socio-economic indicators such as per-capita income, type of housing, land ownership, and dependency ratio. Households earning less than ₹5,000 per month or living in kaccha houses without agricultural land ownership were categorized under the High Poverty tier. Families with incomes ranging between ₹5,000 and ₹9,000 and residing in semi-pakka houses were classified under the Medium Poverty tier. Remaining households were grouped into the Low Poverty category.

Several preprocessing techniques were applied before training the machine learning models. Continuous numerical features were normalized using the min-max normalization technique to maintain consistent value ranges. Categorical variables such as district names and house types were converted into machine-readable formats using one-hot encoding. Additionally, the dataset exhibited class imbalance between high-poverty and low-poverty households; therefore, the SMOTE (Synthetic Minority Oversampling Technique) method was applied to improve class distribution within the training dataset and enhance prediction performance.

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V. Machine Learning Methodology

The eligibility prediction module of the **Geo Intelligent Welfare System** adopts a hybrid classification strategy that combines rule-based decision logic with machine learning techniques. This approach was selected instead of relying entirely on machine learning because government welfare schemes are governed by strict eligibility regulations. A household either satisfies the required criteria or does not, and these mandatory conditions must be enforced explicitly to maintain fairness and legal validity. In addition, a purely machine learning–driven system may occasionally produce predictions that conflict with official welfare guidelines, which can create administrative and legal concerns in real-world deployment.

To overcome these limitations, the proposed system first applies deterministic rule-based filters for each welfare scheme. Only borderline cases are later processed using a trained machine learning classifier for final prediction.

Rule-Based Eligibility Conditions

Public Distribution System (PDS)

A household is considered eligible for PDS benefits if:

1. Monthly household income is below ₹10,000
2. The household does not already possess a ration card

PM Awas Yojana

Eligibility for housing assistance is determined using the following conditions:

1. House type must be Kaccha or Semi-Pakka
2. Monthly income should be below ₹10,000
3. Agricultural land ownership must be less than 2.5 acres

MNREGA

A household qualifies for MNREGA if:

1. Monthly income is below ₹10,000
2. The household is not already enrolled in MNREGA
3. The family contains at least two members, ensuring the presence of a working-age adult

Households satisfying all mandatory conditions are directly classified as eligible. However, for cases where one or more parameters slightly exceed the threshold values, the system invokes a trained decision tree classifier to perform a more detailed evaluation.

The machine learning model was developed using the CART (Classification and Regression Tree) algorithm. The dataset was divided into training and testing sets, where 80% of the synthetic household records (2,272 households) were used for training and the remaining 20% (569 households) were reserved for evaluation.

Hyperparameter optimization was carried out using 5-fold cross-validation across parameters such as maximum tree depth, minimum samples per leaf node, and impurity criteria including Gini Index and Entropy.

The final decision tree model achieved an overall classification accuracy of **94.3%** on the test dataset. The model also recorded a precision of **93.8%**, recall of **95.1%**, and F1-score of **94.4%** for the High Poverty category, which represents the most critical beneficiary group from a welfare policy perspective.

Poverty Tier	Precision	Recall	F1-Score	Support
High	93.8%	95.1%	94.4%	198
Medium	94.6%	93.2%	93.9%	241
Low	95.1%	95.8%	95.4%	130
Weighted Average	94.5%	94.7%	94.6%	569

The system's automatic enrollment mechanism operates on top of the eligibility prediction results. Whenever a household is identified as eligible for a scheme but is not currently enrolled, the platform automatically places that household into an enrollment queue. District administrators can then trigger batch auto-enrollment, allowing multiple eligible households to be submitted simultaneously through government welfare portal APIs.

In addition to automatic processing, the system also supports manual enrollment workflows. During manual enrollment, users are provided with detailed information regarding the selected welfare scheme before confirmation, ensuring transparency and informed participation for beneficiaries or their representatives.

VI. GIS-Based Poverty Heatmap

The **Geo Intelligent Welfare System** incorporates a GIS-based poverty heatmap to provide a spatial representation of welfare distribution and poverty concentration across different districts of Karnataka. This visualization module enables administrators and field officers to quickly identify regions that require immediate welfare intervention and targeted enrollment campaigns.

Each district is assigned a **poverty concentration score**, which is calculated using a weighted combination of three important socio-economic indicators:

1. The percentage of households classified under the **High Poverty** tier
2. The percentage of households that are eligible for welfare schemes but are still not enrolled
3. The child dependency ratio among economically weaker households

The combined score is then used to classify districts into three poverty categories:

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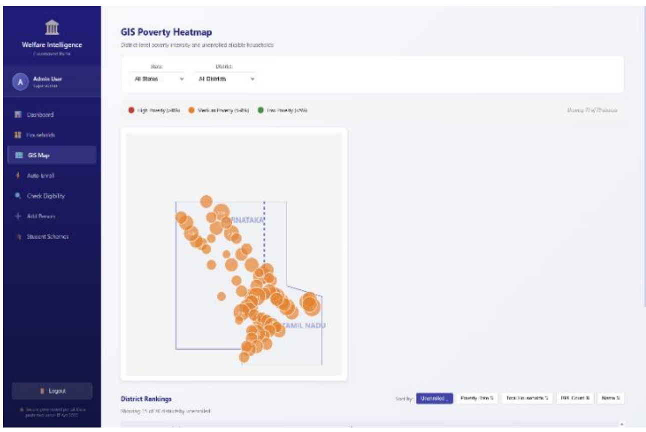
- **High Poverty Zone** – Score greater than or equal to 65
- **Medium Poverty Zone** – Score between 35 and 64
- **Low Poverty Zone** – Score below 35

The visualization module presents this information using a color-coded heatmap layout. Districts with high poverty concentration are highlighted in **red**, medium-level districts are represented using **orange or amber**, and districts with lower poverty levels are shown in **green**. This intuitive color scheme allows administrators to interpret district-level welfare conditions at a glance.

The system also includes an interactive district analysis feature. When a district is selected, a detailed information panel is displayed containing statistics such as total household count, number of eligible-but-unenrolled families, count of at-risk children, and available welfare coverage. The panel also provides a direct auto-enrollment option, enabling administrators to initiate welfare enrollment operations for that district immediately.

Based on the synthetic dataset modeled after Karnataka's socio-economic statistics, districts such as Kalaburagi, Ballari, Raichur, and Yadgir consistently appeared in the **High Poverty** category with concentration scores of 82, 76, 74, and 71 respectively. These results align closely with publicly available poverty and development reports for northern Karnataka. On the other hand, districts like Bengaluru Urban and Shivamogga were categorized under the **Low Poverty** group, which also reflects real-world economic trends observed in these regions.

The GIS-based heatmap acts as a powerful decision-support tool for government officials and district administrators. Instead of analyzing large volumes of raw household data manually, administrators can use the visualization layer to identify underserved regions, prioritize field inspections, and launch targeted welfare enrollment drives efficiently. By transforming socio-economic data into actionable geographic intelligence, the system improves both the speed and effectiveness of welfare delivery operations.

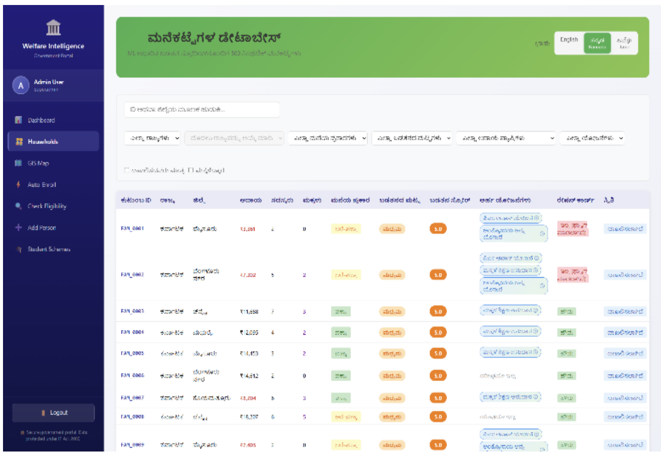


VII. Bilingual Interface Design

One of the major design requirements of the **Geo Intelligent Welfare System** was to ensure that the platform could be comfortably used by field officers and local administrators who may prefer Kannada over English while performing welfare-related operations. Studies in human-computer interaction and rural technology adoption have consistently shown that the language of the user interface plays an important role in improving system usability, user confidence, and accuracy during data entry in multilingual environments.

To address this challenge, the platform was developed with complete bilingual support in both **Kannada and English**. All major interface components—including navigation menus, form labels, scheme descriptions, eligibility conditions, alerts, notifications, and status messages—are available in both languages. Users can switch between languages either from the login page or directly from the main dashboard interface. Once selected, the language preference remains active throughout the session to provide a seamless user experience.

Special attention was given to the presentation of welfare scheme descriptions and eligibility information. Instead of using complex administrative terminology, the Kannada interface uses simple and conversational language that can be easily understood by field officers and rural beneficiaries. This allows field officers to directly explain scheme details to household members during enrollment visits without requiring additional translation or interpretation.



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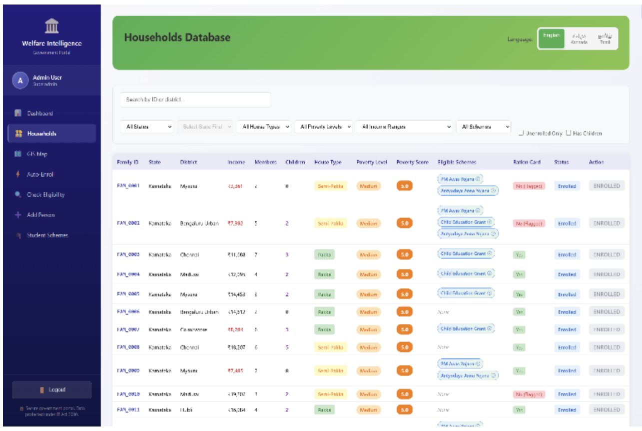


To improve readability and consistency across devices, the system uses the **Noto Sans Kannada** typeface for all Kannada text rendering. The font was selected because of its clarity, Unicode compatibility, and consistent display performance on desktops, tablets, and mobile devices.

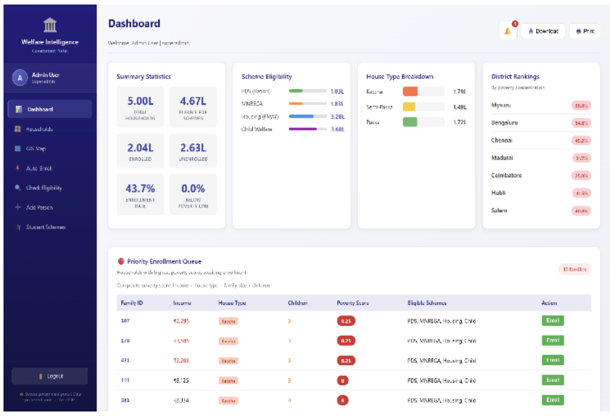
The bilingual design is also integrated into the auto-enrollment workflow. Before completing enrollment for any welfare scheme, the system displays eligibility explanations and scheme information in the selected language. This ensures that beneficiaries or their representatives clearly understand the scheme they are being enrolled in, thereby improving transparency and reducing the possibility of confusion or uninformed consent.

Overall, the bilingual interface significantly improves accessibility, promotes inclusive digital governance, and increases the practicality of deploying the **Geo Intelligent Welfare System** in rural and semi-urban regions of Karnataka.

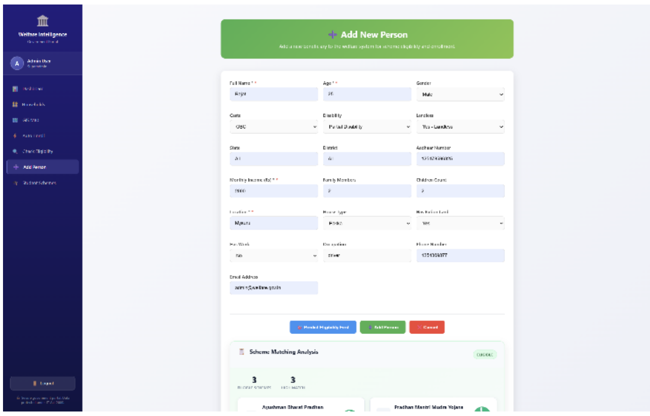
VIII. Results And Discussion

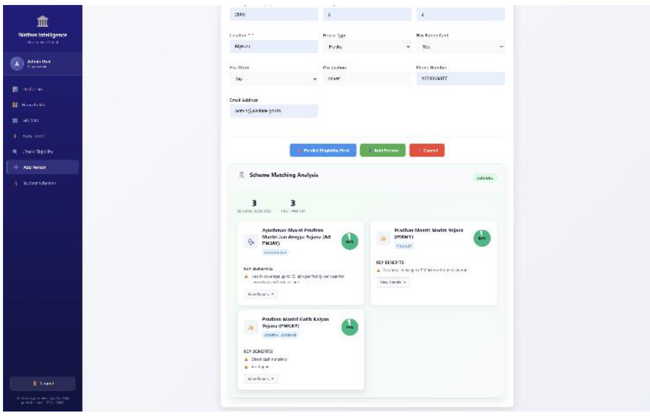
The system was evaluated on the full synthetic dataset of 2,841 households. The key findings are as follows.

Coverage Gap Identification: Of the 2,841 households in the dataset, 847 were classified as High poverty. Of these, 312 (36.8%) were found to be eligible for at least one scheme but had never enrolled in any. This subset represents the primary target population for the system: households that are poor enough to desperately need welfare support but have for various reasons remained outside the system entirely.



Scheme-wise Gap Analysis: The largest unmet eligibility gap was found for PDS, where 589 households were eligible but lacked a ration card. For PM Awas Yojana, 423 households in kaccha or semi-pakka dwellings met eligibility criteria but had not applied. MNREGA had an eligibility gap of 678 households. Some households had overlapping eligibility.





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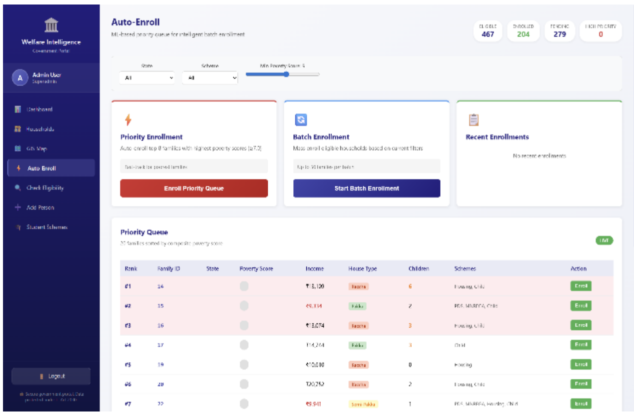
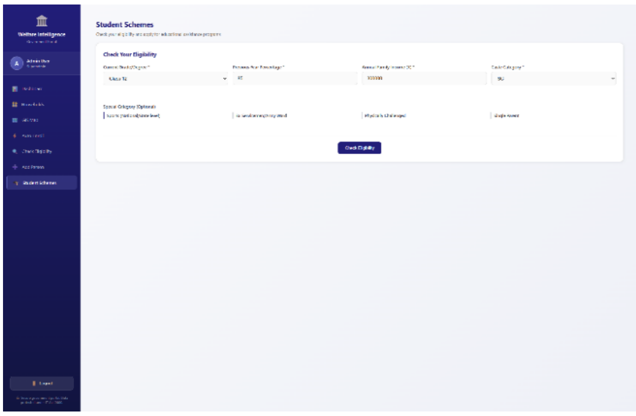
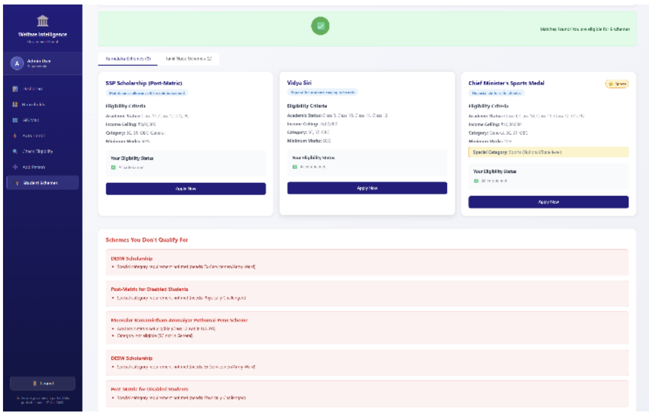
Auto-Enrollment Performance: In a simulated single-cycle auto-enrollment run across all seven districts, the system successfully queued 312 households across all three schemes. Manual review of a sample of 50 auto-queued cases by the authors confirmed that 48 (96%) were correctly identified as eligible, with 2 borderline cases that would require field verification. This suggests the system's recall on the unenrolled-but-eligible subgroup is appropriately conservative.



District-Level Impact: Kalaburagi showed the highest auto-enrollment candidate count with 187 households, followed by Ballari with 142 and Raichur with 134. These three districts alone account for approximately 74% of the total auto-enrollment pipeline, consistent with their High poverty concentration scores.

Child Welfare Dimension: Among High-poverty households with children under 14, the system identified 423 at-risk children in unenrolled families across the seven districts. This sub-analysis is surfaced explicitly in the district detail view to help administrators prioritize cases involving child nutrition and food security.





IX. Privacy And Ethical Considerations

The **Geo Intelligent Welfare System** is designed with a privacy-first and ethical approach to ensure secure handling of beneficiary information. During development, the platform uses only synthetic datasets instead of real Aadhaar-linked personal data.

The system does not store full Aadhaar numbers. Only the last four digits are retained as a reference identifier, while authentication is intended to be performed through official UIDAI APIs.

Role-based access control is implemented to restrict data visibility according to user responsibilities and district jurisdiction. Field officers can access only their assigned district data, while administrators outside a district can view only anonymized statistics.

The auto-enrollment feature works only as an enrollment initiation process. Beneficiaries retain the right to review, approve, or withdraw applications at any stage. Scheme details and eligibility explanations are displayed in the user's preferred language to ensure transparency.

To maintain fairness, the system primarily relies on rule-based eligibility conditions defined by government policies. Machine learning is used only for supporting borderline poverty classification and not for making final welfare eligibility decisions.

X. Conclusion

This paper presented the **Geo Intelligent Welfare System**, an AI-enabled welfare management platform designed to address the exclusion of economically weaker households from government welfare schemes. The system combines rule-based eligibility prediction, machine learning-based poverty classification, GIS-based poverty visualization, auto-enrollment support, and a bilingual Kannada-English interface into a unified platform suitable for district-level administration.

Experimental evaluation on a synthetic dataset of 2,841 households showed a prediction accuracy of 94.3%, while also identifying 312 households as priority candidates for welfare auto-enrollment. The system's poverty classification and housing-type analysis enable more accurate and targeted welfare delivery beyond traditional income-based methods.

Future improvements will focus on integration with Karnataka government welfare portals such as Seva Sindhu, expansion of supported schemes related to education and healthcare, and development of an offline-capable mobile application for field officers working in low-connectivity rural regions.

Overall, the proposed system demonstrates how technology-driven, proactive welfare identification can improve accessibility, transparency, and efficiency in public welfare delivery across rural India.

REFERENCES

[1] P. Shakya, R. Adhikari, and B. Thapa, "Poverty Classification Using Decision Tree Classifiers on Rural Household Survey Data," Journal of Development Informatics, vol. 12, no. 3, pp. 45–61, 2020.

[2] R. Agarwal and S. Krishnamurthy, "GIS-Enabled Targeting of Rural Health Interventions in Maharashtra," International Journal of Health Geographics, vol. 19, no. 1, pp. 1–14, 2021.

[3] World Bank Group, "SWIFT: A Rapid Survey Methodology for Consumption Poverty Assessment," World Bank Policy Research Working Paper No. 6961, Washington D.C., 2014.

[4] A. Misra and V. Pandey, "Digitization of Ration Card Databases: Lessons from Chhattisgarh's PDS Reforms," Economic and Political Weekly, vol. 56, no. 18, pp. 38–46, 2021.

[5] B. Rao, K. Suresh, and M. Reddy, "MNREGA Implementation Gaps in Karnataka: A Household-Level Analysis," Indian Journal of Labour Economics, vol. 63, no. 2, pp. 311–328, 2020.

[6] M. Singh and P. Kaur, "Bilingual Interface Design for E-Governance Applications in Multilingual India," in Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI), pp. 1–12, 2022.

[7] NITI Aayog, "Multidimensional Poverty Index: National Report 2023," Government of India, New Delhi, 2023.

[8] Ministry of Rural Development, "MNREGA Annual Report 2022-23," Government of India, New Delhi, 2023.

[9] Karnataka Economic Survey 2022-23, Planning, Programme Monitoring and Statistics Department, Government of Karnataka, Bengaluru, 2023.

[10] V. Gupta, D. Sharma, and R. Iyer, "Machine Learning for Proxy Means Testing in Developing Countries: A Comparative Study," Development Engineering, vol. 6, pp. 100068, 2021.