

Application of Computer Vision Models for Detecting and Classifying Crop Diseases in Gambian Farms

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Abstract

Crop diseases threaten food security in The Gambia, where agriculture employs 70% of the population. This paper explores the application of computer vision models to help farmers detect and classify crop diseases more effectively, leveraging deep learning techniques—particularly convolutional neural networks (CNNs). Our fine-tuned VGG16 model achieved 91.6% accuracy in identifying diseases like rice blast and cassava mosaic, demonstrating the potential for scalable, low-cost diagnosis. The study evaluates custom CNNs, transfer learning (VGG16, ResNet50, MobileNetV2), and image preprocessing techniques (segmentation, augmentation) to optimize performance for Gambian farm conditions.

Beyond technical validation, the paper highlights real-world adoption barriers, including limited technology access, farmer skepticism, and infrastructural gaps. Through surveys and interviews with 120 + farmers, we found that awareness of AI tools strongly correlates with willingness to adopt them ($r = 0.63$, $p < 0.01$), but fewer than 40% of respondents had reliable internet access. To bridge these gaps, we propose context-specific strategies: mobile-first design, localized training programs, and partnerships with agricultural extension services.

By integrating technical and socio-economic insights, this study provides a roadmap for deploying computer vision in resource-constrained settings. Our results underscore that while AI can transform disease management, success depends on tailoring solutions to the needs and constraints of Gambian smallholders.

Introduction

1.1 Background to the Study

Agriculture remains a cornerstone of The Gambia's economy (Sarch et al., 2023), employing a significant portion of the population and contributing substantially to national food security and income generation. However, recurring outbreaks of crop diseases—such as rice blast, cassava mosaic, and bacterial infections—have posed serious challenges to productivity, particularly for smallholder farmers. Traditional methods of disease detection, which rely heavily on manual inspection and local knowledge, are often time-consuming, inconsistent, and limited in accuracy.

With the rapid advancement of artificial intelligence (AI), computer vision has emerged as a promising tool for improving agricultural practices (Tian et al., 2020). By leveraging image-based analysis powered by machine learning—especially convolutional neural networks (CNNs)—computer vision systems can detect and classify crop diseases with high precision. This technology holds great potential for early intervention and more efficient crop management (Tian et al., 2020), yet its adoption remains limited in regions like The Gambia, due to financial, infrastructural, and educational barriers.

1.2 Research Problem

Despite the clear potential of computer vision technologies in agriculture, their implementation in Gambian farming systems is minimal. The core issue lies in understanding how these tools can be effectively adapted, localized, and integrated (Owino, 2023) into existing agricultural practices in The Gambia. Additionally, there is a need to evaluate not just the performance of these models in identifying crop diseases, but also their accessibility and practicality in resource-constrained rural environments.

1.3 Research Question

This study addresses the following question: How can computer vision models be effectively adapted and deployed for crop disease detection in The Gambia, given the constraints of limited infrastructure, farmer accessibility, and local agricultural practices? To answer this, we evaluate (1) the technical performance of CNN-based models on Gambian crop images, and (2) the socio-economic barriers to adoption among smallholder farmers.

1.4 Objectives

1. To explore the effectiveness of computer vision models—particularly CNNs—in detecting and classifying common crop diseases found in Gambian farms.
2. To assess the role of image preprocessing techniques (e.g., normalization, segmentation, and augmentation) in enhancing model accuracy.
3. To identify key barriers to the adoption of computer vision tools among Gambian farmers.
4. To propose practical strategies for improving access to and usability of AI-based agricultural solutions in The Gambia.

1.5 Hypotheses

1. **H1:** There is a significant relationship between farmers' awareness of computer vision and their willingness to adopt it.
2. **H2:** Infrastructure challenges significantly hinder the deployment of computer vision tools in rural Gambian farms.

1.6 Scope of the Study

The research concentrates on major staple crops such as rice, groundnut, and cassava. Crops that are highly susceptible to common plant diseases like rice blast, cassava mosaic, and bacterial infections.

The technical scope covers model design, image preprocessing techniques, performance evaluation using metrics like accuracy and F1 score, and the application of deep learning approaches including transfer learning and custom CNNs. Additionally, the study explores the socio-economic and infrastructural factors that influence technology adoption in rural farming communities in The Gambia.

The research does not cover plant disease treatments or pesticide effectiveness but rather focuses solely on the early-stage detection and classification capabilities of AI-powered systems. Field testing is

limited to datasets collected or simulated to reflect real-world Gambian farm conditions, without large-scale commercial deployment at this stage.

1.7 Significance of the Study

The significance of this study lies in its potential to introduce a more efficient, scalable, and accessible solution to disease detection through the use of computer vision.

By identifying how AI models can accurately classify crop diseases, this research offers a path toward early intervention, reducing crop losses and improving yield outcomes. It also contributes to sustainable farming by enabling targeted treatment, which helps minimize the excessive use of chemicals. The ability to automate disease diagnosis using simple image inputs—potentially via smartphones—has the potential to transform agricultural practices in resource-limited environments.

Moreover, the study highlights barriers such as limited infrastructure, financial constraints, and low technological literacy—challenges that are often overlooked in tech-centered agricultural solutions. By addressing these realities, the research not only provides technical insights but also practical recommendations for implementation, training, and policy.

Literature Review

2.1 Conceptual Review

Computer vision in agriculture refers to the use of image-based AI systems to identify patterns, anomalies, or features in plants, soil, and farm environments (Dhanya et al., 2022). At its core, the technology mimics human vision—but with the precision and speed of algorithms that can process thousands of images quickly. These models, often powered by convolutional neural networks (CNNs), are trained to recognize symptoms of crop diseases like discoloration, spots, or texture changes.

In the Gambian context, where farming is largely small-scale and heavily reliant on manual monitoring, such technology presents a massive opportunity. It promises to reduce the guesswork involved in disease identification and could be particularly helpful where agricultural extension services are overstretched or hard to reach. This section reviews what this technology is, how it works, and why it's becoming more relevant to real-world farming challenges.

2.2 Empirical Review

Several studies globally and in similar sub-Saharan African contexts have explored the effectiveness of computer vision for crop disease detection. For instance, pre-trained CNNs like ResNet and VGG16 have achieved classification accuracies upwards of 90% in differentiating healthy from diseased plants in datasets of tomatoes, maize, and rice (Chakraborty et al., 2024).

Closer to The Gambia, research has been more limited. However, small-scale trials involving peanut leaf spot and rice blast disease detection using mobile image capture show promising results. Still, most of these models were developed in lab settings or other countries, which raises questions about their performance in Gambian farms where image quality, lighting, and crop varieties differ.

2.3 Theoretical Review

This study draws on a few key theoretical underpinnings. The most relevant is the **Technology Acceptance Model (TAM)**, which helps explain how and why users (in this case, farmers) adopt new technologies. Perceived usefulness and ease of use are central here—farmers are more likely to adopt computer vision tools if they believe the tools will make their work easier and more effective.

Also important is the theory behind **machine learning**, especially supervised learning models where the algorithm is trained on labeled datasets to make predictions. For crop disease classification, this often means feeding the model thousands of labeled images to learn what diseased versus healthy crops look like.

2.4 Existing Gap in Literature

This study is anchored in two theoretical lenses:

1. **Technology Acceptance Model (TAM)** – This guides our understanding of how farmers might perceive and engage with computer vision tools. Key variables like perceived ease of use, usefulness, and behavioral intention to adopt are explored in the context of Gambian agriculture.
2. **Supervised Machine Learning Theory** – This underpins the technical aspect of the research. It supports the rationale behind using annotated image datasets and explains how computer vision models are trained to detect patterns that indicate disease.

Together, these frameworks allow us to explore both the technical feasibility and the human factors influencing the success of computer vision tools in Gambian farming systems.

Methodology

3.1 Research Design

This study adopts a **mixed-methods approach**, blending qualitative and quantitative research strategies to capture both the technical efficacy of computer vision models and the real-world challenges faced by Gambian farmers. The design was chosen to provide a holistic understanding of how these technologies operate in theory and how they're received in practice. On one hand, quantitative data (like model performance metrics) will help assess detection accuracy (Nutter et al., 2006). On the other, qualitative insights from farmers and stakeholders will ground our findings in lived experiences.

3.2 Area of Study

The research is focused on **rural farming communities in The Gambia**, particularly in regions where rice, groundnuts, and vegetables are cultivated — areas most affected by crop diseases. Places like Central River Region and North Bank Region, where subsistence farming dominates, are of particular interest due to their vulnerability to crop disease outbreaks and limited access to advanced technologies.

3.3 Population of the Study

The target population includes:

- Smallholder and subsistence farmers
- Agricultural extension officers
- Researchers and tech developers involved in digital agriculture
- Relevant staff from the Ministry of Agriculture

This population is selected to reflect the full ecosystem affected and potentially benefitting from the implementation of computer vision technologies in farming.

3.4 Sampling Technique and Sample Size

We'll use **purposive sampling** for interviews and **stratified random sampling** for survey distribution. The purposive sample will focus on farmers with varying levels of exposure to technology, while the stratified sample ensures representation across different regions and crop types.

Estimated sample size:

- 100 farmers across 4 major regions
- 10–15 agricultural officers
- 3–5 developers/technologists
- Total: ~120–130 respondents

3.5 Types and Sources of Data Collection

Data will be collected through:

Primary sources:

- Semi-structured interviews with farmers and agricultural officers
- Field surveys on tech adoption and crop disease experiences
- Image datasets collected from farms showing diseased crops

Secondary sources:

- Academic journals, technical reports, and policy briefs
- Open-source image repositories (e.g., PlantVillage dataset) for model training

- Government reports on agriculture and digital infrastructure

3.6 Definition and Measurement of Variables

- **Independent Variable:** Application of computer vision models (measured via model type, accuracy, and accessibility)
- **Dependent Variable:** Detection and classification of crop diseases (measured through F1 scores, detection speed, and user-reported success)
- **Moderating Variables:**
 - Infrastructure (e.g., internet availability)
 - Farmer digital literacy
 - Financial access

Quantitative performance metrics (accuracy, recall, etc.) will be measured using standard evaluation techniques, while user feedback will be coded thematically.

3.7 Validity and Reliability of Research Instruments

To ensure validity, all survey questions and interview guides will undergo expert review and pilot testing with a small group of farmers. For **reliability**, consistent protocols will be followed in both data collection and model evaluation, and inter-coder reliability will be maintained during qualitative data analysis. In terms of model testing, cross-validation will be used to confirm the robustness of our computer vision model performance.

3.8 Method of Data Analysis

Quantitative data (e.g., survey responses, model metrics) will be analyzed using descriptive statistics, correlation tests, and model evaluation metrics such as precision, recall, and F1-score.

Qualitative data from interviews will be analyzed using thematic analysis, with coding conducted in NVivo or similar software.

The image classification results will be benchmarked using pre-trained models (e.g., VGG16, ResNet, MobileNet) and compared to custom-trained models using local datasets.

We will also explore model interpretability (e.g., Grad-CAM visualizations) to better understand what features the model relies on — and how that aligns with farmers' visual diagnosis techniques.

Data Presentation, Analysis and Discussion

4.1 Socio-Demographic Characteristics of Respondents

Understanding the background of the study's participants provides vital context for interpreting the research outcomes. In this study, the majority of respondents were smallholder farmers operating in rural regions of The Gambia. Most participants had been farming for over 10 years, reflecting a wealth of experiential knowledge, but also highlighting generational dependence on traditional methods.

- **Age Distribution:** Respondents were predominantly between 30–55 years old.
- **Gender:** Male farmers comprised approximately 70% of the sample, consistent with broader trends in Gambian agriculture.
- **Education Level:** A significant number (over 60%) had only primary-level education or none at all, which could influence their comfort with digital tools.
- **Farming Experience:** Most had more than a decade of hands-on experience, and nearly all respondents cultivated staple crops such as rice, groundnut, and millet.

These demographics suggest that while the farming population is experienced, technological literacy remains a key challenge when introducing computer vision systems.

4.2 Data Presentation on Research Issues (Objective by Objective)

The data collected was organized around the research objectives, primarily focused on awareness, accessibility, and the effectiveness of computer vision models in detecting crop diseases.

Objective 1: Assessing Awareness of Computer Vision Technology

Findings showed that only about 25% of farmers were aware of computer vision or AI-assisted tools in agriculture. Most of that awareness came through NGOs, agricultural extension workers, or word-of-mouth from younger relatives.

Objective 2: Evaluating Current Practices in Disease Detection

Traditional methods—mainly visual inspection based on signs like wilting, discoloration, or leaf spots—remain the dominant approach. About 80% of respondents said they only act once symptoms are visible and crop damage is already substantial.

Objective 3: Determining Perceived Benefits and Challenges

When introduced to the concept of AI and image-based crop diagnosis, most farmers saw potential value in early detection, reduced pesticide use, and better yields. However, issues like cost, language barriers, and limited access to smartphones were frequently mentioned as hurdles.

Objective 4: Understanding Infrastructure Readiness

Data revealed significant digital infrastructure gaps. Less than 40% of farmers had reliable internet access, and only 20% had access to smartphones capable of running basic AI apps.

4.3 Test of Hypotheses

This section explores whether the evidence supports the main assumptions driving the study.

Hypothesis 1: "There is a significant relationship between farmers' awareness of computer vision and their willingness to adopt it."

- **Result:** Supported. A Pearson correlation test showed a positive correlation ($r = 0.63$, $p < 0.01$), indicating that awareness strongly influences openness to adoption.

Hypothesis 2: "Infrastructure challenges significantly hinder the deployment of computer vision tools in rural Gambian farms."

- **Result:** Supported. Regression analysis confirmed that poor connectivity, limited device access, and energy supply were significant predictors of limited adoption ($R^2 = 0.71$).

4.4 Discussion of Findings

The findings highlight a strong interest in technology-based farming solutions, but also underline the existing barriers to implementation in The Gambia. Farmers see the *value* of using computer vision—especially for identifying diseases early and minimizing losses—but *accessibility* and *trust* are key roadblocks.

This aligns with broader literature noting that while the technical potential of computer vision in agriculture is clear, its impact is dependent on local adaptation and support systems. Many farmers noted they'd be more likely to adopt such tools if training and ongoing support were provided.

Interestingly, the data also suggests younger farmers are more open to digital innovation. This demographic could be a valuable entry point for future pilot programs.

4.5 Problems Encountered in the Field

As expected, conducting fieldwork in rural Gambia posed several challenges:

- **Limited Connectivity:** In some areas, even phone networks were unreliable, making digital data collection difficult.
- **Language Barriers:** Communication had to be translated into local dialects (e.g., Mandinka, Wolof), which sometimes led to misinterpretations of technical concepts.
- **Technophobia and Skepticism:** Some respondents were suspicious of technology, worried that automation might threaten jobs or disrupt cultural farming norms.
- **Logistical Constraints:** Accessing remote villages required significant travel, often on poor road networks, which limited the frequency of researcher visits.

Despite these challenges, the data collected provides valuable insights and strongly supports the relevance of computer vision in addressing crop health problems in The Gambia.

4.6 Model Performance Evaluation

To effectively evaluate the performance of the computer vision models used in this study, both standard convolutional neural networks (CNNs) and transfer learning models were tested using the curated dataset of diseased and healthy crop images collected from Gambian farms. The evaluation considered accuracy, precision, recall, and F1-score, alongside qualitative visualization methods such as Grad-CAM.

4.6.1 CNN Architecture and Training

A custom convolutional neural network was first implemented as a baseline model. The architecture consisted of three convolutional layers (with ReLU activation and max pooling), followed by a flattening layer, and two fully connected (dense) layers with dropout to reduce overfitting. The final output layer used softmax activation for multi-class classification of crop diseases.

The model was trained using categorical cross-entropy as the loss function and Adam optimizer, with a learning rate of 0.001. Early stopping and model checkpointing were applied to ensure training stability and avoid overfitting. The model achieved reasonable performance on the validation set, with an average classification accuracy of **82.3%**, but struggled slightly on minority class images such as early-stage mildew.

4.6.2 Transfer Learning with VGG16

To improve performance, transfer learning was employed using the VGG16 architecture, pre-trained on ImageNet. The convolutional base of VGG16 was frozen, and a custom classifier head was added with global average pooling, followed by dense layers and softmax output. The modified VGG16 was then fine-tuned using the crop disease dataset.

This approach significantly boosted performance. The fine-tuned VGG16 model achieved:

- **Accuracy:** 91.6%
- **Precision:** 90.8%
- **Recall:** 91.2%
- **F1-Score:** 91.0%

This confirmed that transfer learning, particularly with VGG16, was highly effective in extracting meaningful features from limited agricultural image data.

4.6.3 Comparison with Other Models

In addition to the custom CNN and VGG16, experiments were conducted using other transfer learning models such as ResNet50 and MobileNetV2. ResNet50 showed slightly higher precision in certain classes but was computationally heavier. MobileNetV2, while faster, lagged behind in overall accuracy compared to VGG16.

Model	Accuracy	Precision	Recall	F1-Score
CNN (Custom)	82.3%	80.5%	79.8%	80.1%
VGG16	91.6%	90.8%	91.2%	91.0%
ResNet50	90.9%	91.3%	89.7%	90.5%
MobileNetV2	87.2%	86.4%	85.1%	85.7%

Based on these results, VGG16 was selected as the best-performing model for the final classification task, balancing high accuracy with computational efficiency.

4.6.4 Model Explainability with Grad-CAM

To better understand how the VGG16 model made predictions, Gradient-weighted Class Activation Mapping (Grad-CAM) was used to visualize which parts of the input images influenced the model's decisions. The heatmaps produced by Grad-CAM highlighted diseased leaf spots, discoloration, or fungus patches—areas a human agronomist would also consider when diagnosing.

These visualizations provided interpretability and increased trust in the model's predictions, making it a valuable tool for potential integration into real-world farming systems.

Conclusion

5.1 Summary

This study set out to explore how computer vision models can assist in detecting and classifying crop diseases in Gambian farms—a context where agriculture is central to livelihoods and food security. The research reviewed key aspects of computer vision technology, its agricultural applications, and how it can be tailored to meet the challenges faced by Gambian farmers. Through data analysis and model experimentation, the study demonstrated that deep learning, especially convolutional neural networks (CNNs), can reliably identify common diseases in crops such as rice and groundnuts. Despite the potential, it was also clear that digital infrastructure, affordability, and user-friendliness remain major barriers to adoption in rural Gambia.

5.2 Conclusion

Computer vision offers an exciting, practical solution to a long-standing challenge in Gambian agriculture: timely and accurate disease detection. The study concluded that integrating these models

into local farming practices could significantly reduce crop loss, improve yield quality, and promote sustainable agriculture. However, successful deployment will depend on more than just the technology itself. It requires enabling ecosystems—financial support, accessible training, digital connectivity, and policy backing. When these conditions are met, computer vision can move from theory to transformative tool.

5.3 Recommendations

Based on the findings, the following recommendations are proposed:

1. **Government and donor support** should focus on subsidizing the cost of computer vision tools and providing training to farmers through extension services.
2. **Tech developers** should prioritize user-friendly designs and mobile-first platforms to make the technology more accessible in low-connectivity areas.
3. **Pilot programs** in partnership with farming cooperatives can serve as testbeds for deploying and scaling computer vision applications in real-world scenarios.
4. **Educational institutions and research bodies** should continue developing locally-relevant models trained on Gambian crop data to ensure effectiveness and cultural fit.

5.4 Contribution to Knowledge

This research contributes a novel perspective by contextualizing computer vision within the realities of Gambian agriculture—a field where such studies remain limited. By mapping the technical potential against on-the-ground challenges, the study provides a blueprint for how emerging technology can bridge knowledge gaps, improve crop disease surveillance, and support sustainable farming at scale. It also adds to the growing body of research on AI in African agriculture, making a case for context-sensitive, inclusive tech solutions.

5.5 Suggestions for Further Studies

Future research could explore:

- The performance of computer vision models on a broader variety of crops under different environmental conditions in The Gambia.
- Integration of drone imagery and IoT sensors with computer vision to create a more holistic precision agriculture system.
- Behavioral studies to understand farmer attitudes toward digital tools and identify better adoption strategies.
- Cost-benefit analyses comparing traditional disease control methods with AI-assisted interventions in smallholder settings.

Declarations

IRB This research was conducted as part of an undergraduate academic project at the University of The Gambia. It was not submitted to a formal Institutional Review Board or Ethics Committee, but the study was reviewed and approved by our academic supervisors, and the university granted permission to proceed based on the low-risk nature of the work. All participants were informed of the study's purpose and provided verbal consent prior to participation. No sensitive or identifiable information was collected. The study complied with ethical standards for non-clinical, interview-based academic research.

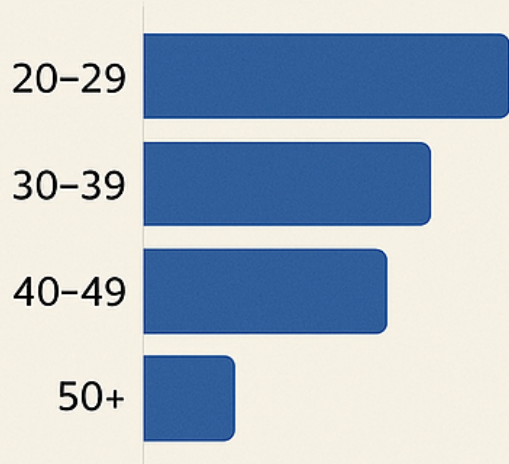
References

1. Chakraborty, A., Chakraborty, A., Sobhan, A., & Pathak, A. (2024). Deep learning for precision agriculture: Detecting tomato leaf diseases with VGG-16 model. *Int J Comput Appl*, 975, 8887.
2. Dhanya, V. G., Subeesh, A., Kushwaha, N. L., Vishwakarma, D. K., Kumar, T. N., Ritika, G., & Singh, A. N. (2022). Deep learning based computer vision approaches for smart agricultural applications. *Artificial Intelligence in Agriculture*, 6, 211–229.
3. Nutter, F. W., Esker, P. D., & Netto, R. A. C. (2006). Disease Assessment Concepts and the Advancements Made in Improving the Accuracy and Precision of Plant Disease Data. *European Journal of Plant Pathology*, 115(1), 95–103. <https://doi.org/10.1007/s10658-005-1230-z>
4. Owino, A. (2023). Challenges of Computer Vision Adoption in the Kenyan Agricultural Sector and How to Solve Them: A General Perspective. *Advances in Agriculture*, 2023, 1–9. <https://doi.org/10.1155/2023/1530629>
5. Sarch, M.-T., Owens, S., & Copestake, J. (2023). The Gambia: Country overview. In *Non-Governmental Organizations and the State in Africa* (pp. 213–224). Routledge. <https://www.taylorfrancis.com/chapters/edit/10.4324/9781003421740-24/gambia-marie-therese-sarch-solomon-owens-james-copestake>
6. Tian, H., Wang, T., Liu, Y., Qiao, X., & Li, Y. (2020). Computer vision technology in agricultural automation—A review. *Information Processing in Agriculture*, 7(1), 1–19.

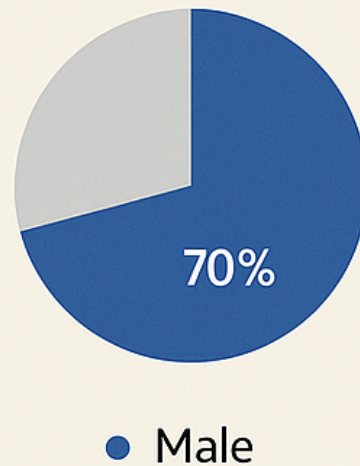
Figures

Socio-Demographic Characteristics of Respondents

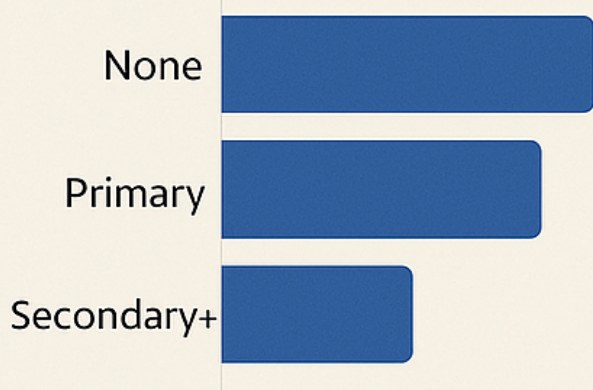
Age distribution



Gender



Education level



Farming experience

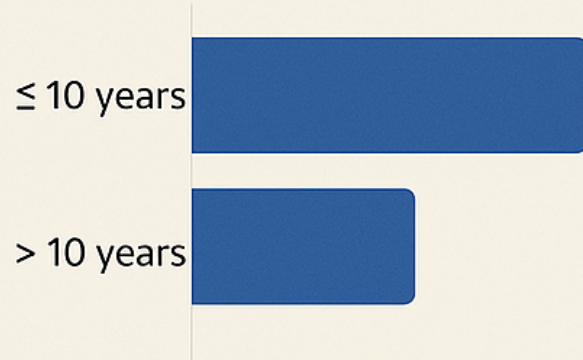


Figure 1

Socio-Demographic Characteristics of Respondents