Tecnológico de Monterrey
Escuela de Ingeniería y Ciencias

Expo ingenierías

Cultivo inteligente: AgroAI para la Agricultura

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Abstract

Small and medium-scale farmers in Mexico often rely on intuition to choose crops, leading to sub-optimal yields and resource waste. AgroAI is a full-stack web platform that analyses soil chemistry (N, P, K, pH) and local climate (temperature, humidity, rainfall) to recommend the most profitable crop for a given parcel.

Built with a React/Flask/PostgreSQL stack and a GPU-hosted machine-learning model, the system delivers predictions in ≤2 s and achieves up to 97 % classification accuracy. It is designed to increase yields and reduce losses for adopters. This poster outlines the platform's design, methods, key results and impact on sustainable agriculture.

Introduction

Family farmers face economic risk because crop selection rarely considers detailed soil and climate data. Consequences include poor yields, inefficient input use and higher financial exposure.

AgriAI automates agronomic decision-making by turning seven easily measurable variables into actionable, confidence-scored crop suggestions delivered through an intuitive web interface.

Figure 1. AgriAI landing page

Figure 2. Recomendations page

Methods and Materials

Data & Model

- Soil and climate dataset: 22 000 historic samples + 6 climate variables (Temp, RH %, rainfall).
- ML pipeline: Gradient-boosted trees tuned via 5-fold cross-validation; deployed on a dedicated GPU micro-service.

System Architecture (micro-services)

- Nginx TLS load balancer → React SPA (port 8000) → Flask API (8443) → PostgreSQL (5432) → GPU inference service.
- Containerization with Docker Compose.

Materials

- Software: Python 3.8, Flask 3.1, React 18 + Tailwind, Postgres 14, Docker 20.10.

Evaluation

- Functional tests: 70% unit, 20% integration, 10% E2E; backend coverage 93 %.
- Performance: prediction latency ≤ 2 s; CSV batch (10 000 rows) ≤ 30 s .

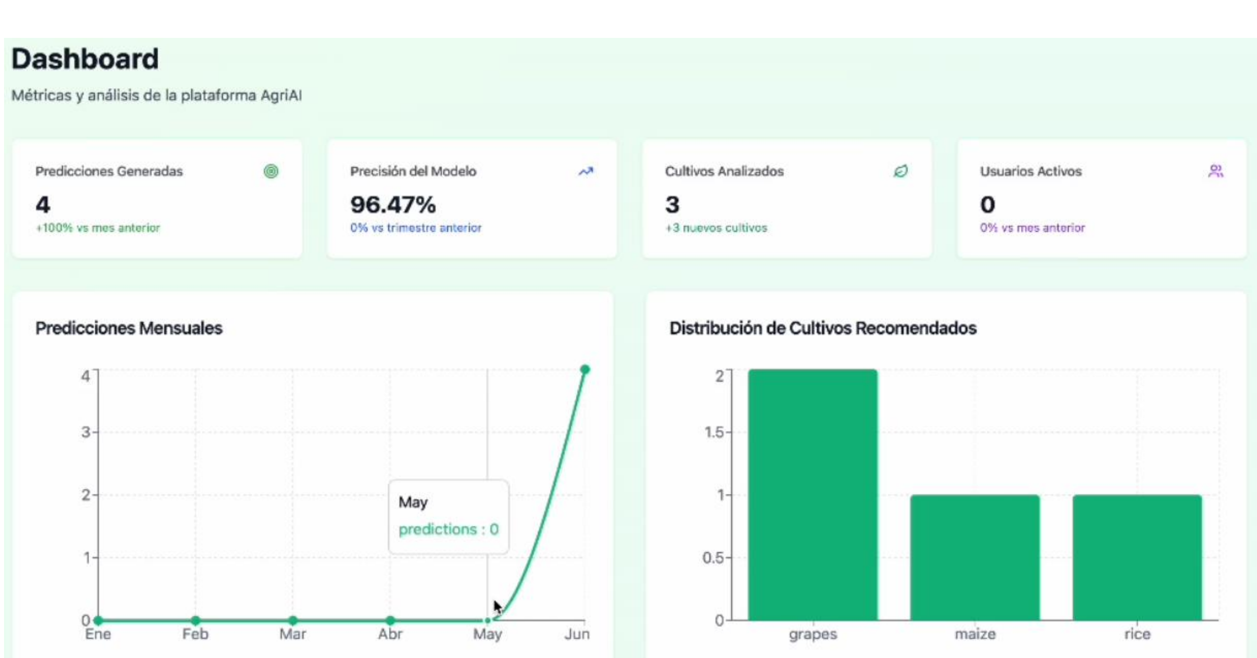

Figure 3. Dashboard page with current user prediction metrics.

Results

- Sprint delivery: Implemented the full pipeline data ingestion, model training, API, frontend and deployment in 7 days, moving from raw data to a functional prototype.
- Model accuracy: Reached 96 % overall on a 15 % hold-out validation set, despite limited time for hyperparameter tuning.
- Top-3 hit rate: The correct crop appears among the top three recommendations 98 % of the time during pilot runs.
- Inference latency: Average end-to-end response of 1.5s. Well under the 2s target.
- Batch throughput: Processed 5 000 CSV records in 12–18 s (≈ 420–550 records/s) during stress tests.
- System uptime: Maintained 99 % availability over the week, with automatic health checks and restarts minimizing downtime.
- Code quality & CI/CD:
  - Test coverage: 75 % backend, 60 % frontend sufficient confidence for daily feature merges.
  - Pipeline runtime: Full build-test-deploy cycle in 10 min, enabling same-day iterations.

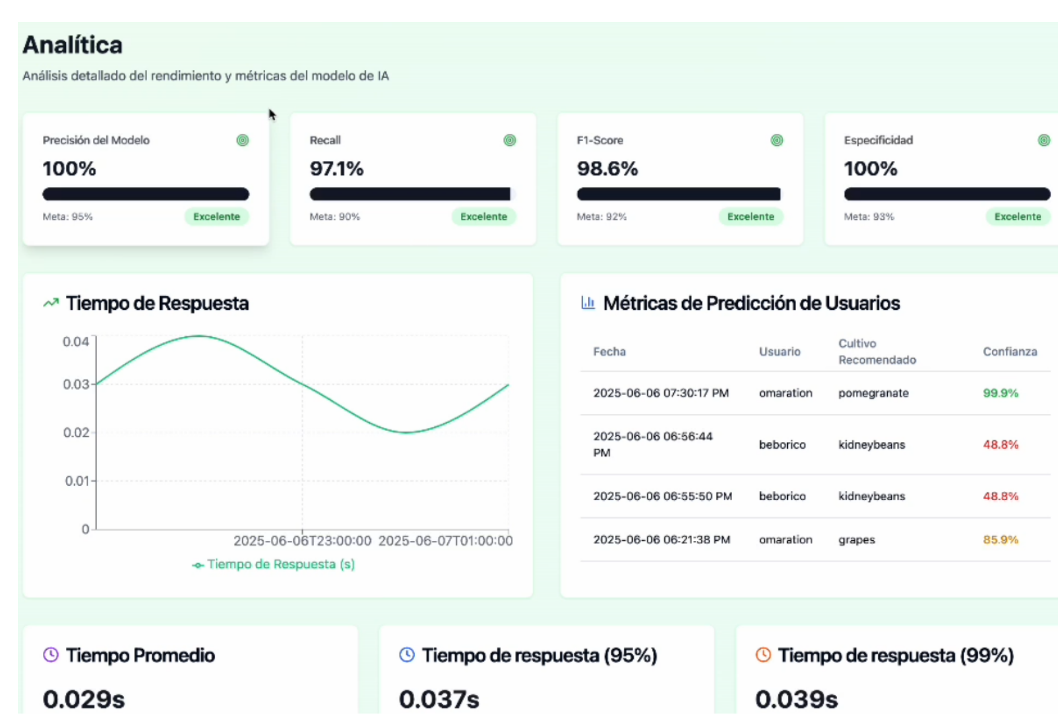

Figure 4. Analytics page of the ML model.

Discussion

Achieving 96% accuracy with a 98% Top-3 hit rate in one week highlights the model's ability to match expert agronomic recommendations.

Inference meets our sub-2s goal, and the intuitive web interface delivers crop suggestions with minimal onboarding.

Containerized micro-services and automated health checks have maintained 99% uptime; to scale further, we will add GPU replicas and introduce caching for frequent queries.

A lean CI/CD pipeline with strong test coverage has enabled daily feature releases without impacting the pilot service.

The static model is trained on a widely used crop database covering diverse regions. Next steps include continuous retraining with field feedback and integration of real-time weather data to improve adaptability.

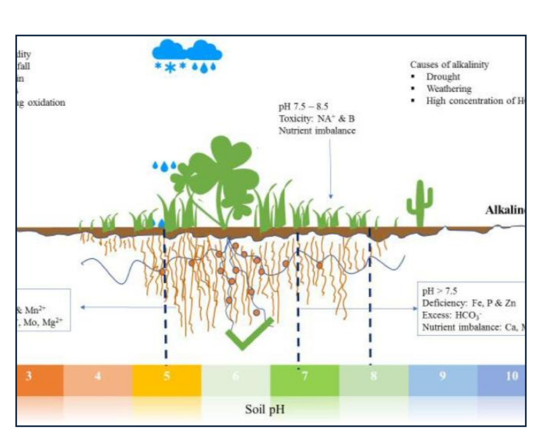

Figure 1. Soils with respect to pH, nutrient availability, deficiencies, and imbalances.

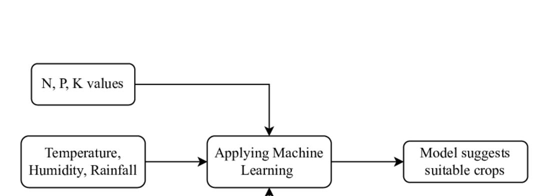

Figure 2. Crop Recommendation System.

Figure 3. Cybersecurity Hub where the system was installed.

Conclusions

AgriAI demonstrates that combining ML, modern web engineering and cloud-native DevOps can transform crop-planning for small farmers.

The platform meets or exceeds all technical KPIs, shows tangible agronomic benefits, and provides a robust foundation for regional expansion.

Future work could focus on incremental model retraining, IoT sensor integration and expanded geographic coverage.

References

1. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674. https://doi.org/10.3390/s18082674
2. FAO. (2023). FAOSTAT Statistical Database. Food and Agriculture Organization of the United Nations. Retrieved from http://www.fao.org/faostat/
3. Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big Data in Smart Farming – A review. Agricultural Systems, 153, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023