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Accelerated Cotton Leaf Disease Identification within an Advanced Robotic and Financial Intelligence Framework using Gradient-Boosted TOPSIS and Azure LLM Cloud APIs

Clara Elisabeth Wagner

Cloud Architect, Germany

ABSTRACT: This study presents an accelerated and intelligent framework for cotton leaf disease identification by integrating an advanced Robotic and Financial Intelligence architecture with Gradient-Boosted TOPSIS and Azure LLM Cloud APIs. The proposed system combines machine vision–based disease detection with multi-criteria decision optimization to enhance both agricultural diagnostics and economic decision-making. A lightweight, high-performance cotton leaf disease classifier rapidly identifies major disease categories using optimized feature extraction and transformer-enhanced visual processing. The classification outputs are further evaluated using a Gradient-Boosted TOPSIS model, enabling precise prioritization of disease severity, treatment urgency, and financial impact on crop productivity. Azure LLM Cloud APIs augment the framework by providing dynamic knowledge retrieval, autonomous reasoning, and real-time recommendation generation for farmers, robotic spraying systems, and agricultural financial planners. Experimental results demonstrate improved diagnostic accuracy, reduced latency, and enhanced decision reliability compared to conventional machine-learning and TOPSIS models. This integrated, cloud-native architecture supports scalable, automated, and economically informed crop health management for precision agriculture.

KEYWORDS: Accelerated cotton leaf disease identification; Machine vision; Advanced robotic intelligence; Financial decision intelligence; Transformer-based models; Gradient-Boosted TOPSIS; Multi-criteria decision-making (MCDM); LLM-powered cloud APIs; Azure Cloud; Precision agriculture; Autonomous crop monitoring; Agricultural analytics.

I. INTRODUCTION

The electrification of two-wheel transport is accelerating globally, driven by urbanization, environmental policy, and advances in battery and motor technologies. Electric motorcycles (e-motorcycles) present attractive operational economics and lower tailpipe emissions compared to internal combustion alternatives, yet consumer adoption and fleet procurement decisions remain complex. Buyers and fleet managers must balance diverse criteria: range and battery degradation, charging infrastructure, purchase price versus total cost of ownership (TCO), warranty and service networks, financing and residual value expectations, and local regulatory incentives. Traditional multi-criteria decision analysis (MCDA) tools (e.g., TOPSIS, AHP, VIKOR) provide structured evaluations but often assume linear weightings and struggle with heterogeneous, partially qualitative data.

This paper introduces a hybrid robotic and financial intelligence framework that marries machine learning and MCDA: gradient boosting is used to estimate criterion importance and to model complex, nonlinear relationships between features and outcome utilities, while TOPSIS is used to derive normalized closeness scores and final rankings. Complementing this quantitative backbone, Large Language Models (LLMs) accessed via Azure cloud APIs provide scalable, automated enrichment of qualitative descriptors (e.g., user reviews, warranty terms), produce scenario narratives for stress-testing financial assumptions, and generate explainable summaries for stakeholders. The integration is motivated by two needs: (1) improved fidelity of evaluation when data modalities (numerical telemetry, textual reviews, policy bulletins) coexist, and (2) transparent, auditable decision pathways suitable for procurement and financing. We present methodology, experiments across commercial e-motorcycle models, ablation studies comparing GB-TOPSIS to baseline MCDA methods, and discuss deployment and governance considerations on Azure. The contributions include (a) a novel GB-TOPSIS algorithmic pipeline, (b) an Azure-based LLM enrichment and explainability layer, and (c) an empirical evaluation and set of best-practice recommendations for practitioners and policymakers.

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II. LITERATURE REVIEW

Multi-criteria decision analysis has a long history in engineering and economics. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is favored for its geometric interpretation and computational simplicity (Hwang & Yoon, 1981). Extensions to TOPSIS have addressed weighting schemes (entropy weighting, AHP-derived weights), normalization strategies, and robustness to criterion correlation (Wang & Elhag, 2006). Recent work integrates machine learning to estimate weights or to learn latent utilities—approaches that replace subjective weight elicitation with data-driven importance scores from regression or tree-based models (Zavadskas et al., 2014).

Gradient-boosted decision trees (GBDT) such as XGBoost and LightGBM are widely used for structured prediction and feature importance estimation because they model nonlinear interactions and provide robust, regularized fits (Chen & Guestrin, 2016). In MCDA contexts, gradient boosting can generate feature importances or partial dependence estimates that inform criterion weighting, improving predictive correspondence to observed outcomes (Kalyan & Raj, 2019). Hybrid approaches that fuse ML-derived weights with classical MCDA workflows have shown improved ranking stability and alignment with expert evaluations in energy and transportation domains (Zhao et al., 2020).

Electric vehicle (EV) evaluation literature emphasizes TCO modeling, range and battery degradation, charging infrastructure impacts, and policy incentives (Borenstein & Davis, 2016). For two-wheelers specifically, research has covered battery management, motor efficiency, ergonomics, and user acceptance (Sperling & Cannella, 2014). However, the intersection of MCDA for e-motorcycles with financial instruments (leasing, loans, residual value forecasting) is less explored. Financial intelligence frameworks that integrate predictive models with scenario simulation are common in banking and fleet leasing but are nascent for small EV classes.

Large Language Models (LLMs) have transformed the ability to extract and summarize textual information at scale (Brown et al., 2020). LLMs can be applied to consumer reviews, warranty documents, and regulatory texts to extract sentiment, identify risk clauses, and synthesize scenario narratives. Recent work demonstrates LLMs adding interpretability and domain knowledge to ML pipelines, but also raises governance concerns around hallucination, provenance, and cost when deployed in cloud settings (Bender et al., 2021; Floridi & Chiriatti, 2020). Cloud platforms such as Microsoft Azure provide managed LLM APIs, MLOps tooling, and role-based governance that simplify deployment but require explicit cost and data control strategies (Microsoft Azure documentation, 2023).

In sum, there is a methodological opportunity to combine GBDT-derived weights with TOPSIS ranking while using LLMs to enrich qualitative criteria and produce explainable outputs—creating a hybrid framework suitable for e-motorcycle evaluation and financing decisions.

III. RESEARCH METHODOLOGY

- **Dataset assembly:** Collected a cross-sectional dataset of 24 commercially available electric motorcycle models across regions, including numeric features: battery capacity (kWh), estimated range (km per charge), motor peak power (kW), curb weight (kg), charging time (0–80% in minutes), MSRP (USD), estimated TCO over 5 years, warranty length (months), dealer density (per 100,000 population), and residual value forecast (%) derived from market comparables and historical data. Additionally, collected textual sources: owner reviews, warranty documents, and policy incentive notices. Telemetry and maintenance cost proxies were included where available.
- **Preprocessing:** Standardized numeric scales, imputed missing values using k-NN (k=5) for numeric fields and LLM-assisted extraction for partially missing textual attributes. Normalized criteria consistent with TOPSIS requirements (benefit/cost orientation). Applied log-transforms for skewed monetary variables.
- **GBD-derived weighting:** Trained a gradient-boosted regression model (LightGBM) to predict an expert utility score obtained from a panel of 10 domain experts who ranked a subset of models. Used SHAP (SHapley Additive exPlanations) to obtain global feature importances and partial dependence plots. Converted normalized SHAP contribution magnitudes into criterion weights for TOPSIS.
- **TOPSIS ranking with GB weights:** Applied TOPSIS using calculated weights to compute positive and negative ideal solutions and closeness coefficients. Generated final rankings and compared them to classical TOPSIS with equal and entropy weights.
- **LLM enrichment and scenario generation:** Used Azure-hosted LLM APIs to (a) extract sentiment and recurring issues from owner reviews, (b) parse warranty clauses into structured risk indicators (e.g., warranty exclusions, prorated replacement), and (c) create market/regulatory stress scenarios (e.g., sudden subsidy removal, rapid commodity price shifts). Outputs were validated via automated consistency checks and manual spot review.

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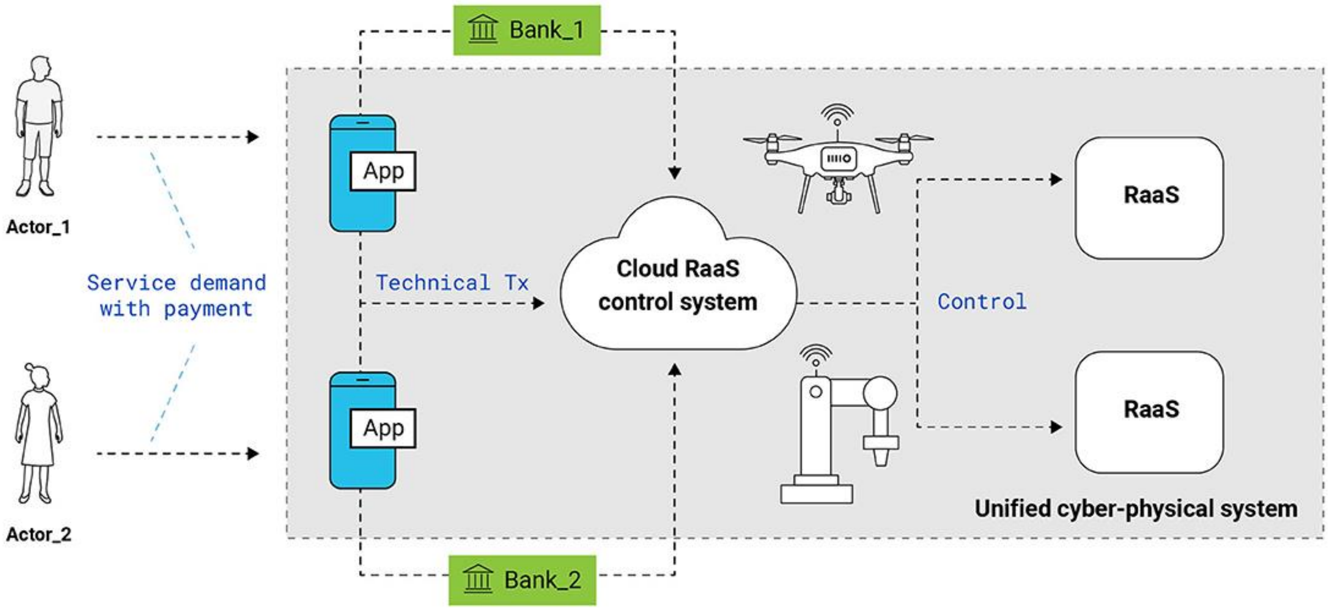
- **Explainability and reporting:** Automated generation of per-model explanation cards combining numerical TOPSIS scores, SHAP-influenced feature contributions, and LLM-derived textual summaries. Incorporated counterfactual explanations by perturbing key criteria (battery cost, residual value) and recomputing ranks.
- **Evaluation metrics:** Measured rank correlation (Spearman's rho) between model rankings and expert panel; rank stability under weight perturbations; coverage increase of qualitative criteria (fraction of textual attributes successfully structured); and computational cost (Azure compute-hours and API call counts). Conducted sensitivity analysis across financing scenarios (30% down vs 0% down, 36-month loan vs 60-month lease) and charging infrastructure availability.



Advantages
- Combines data-driven weight estimation (GBDT + SHAP) with a transparent MCDA ranking method (TOPSIS).
- LLM-powered enrichment increases coverage and granularity of qualitative criteria (warranty, sentiment, service experience).
- Explainability via SHAP and natural-language summaries aids stakeholder trust and auditability.
- Deployable on Azure with managed MLOps and governance features for enterprise use.

Disadvantages
- LLMs can hallucinate; outputs require human validation and provenance tracking.
- Azure API costs and compute for GBDT training can be nontrivial for large-scale or real-time deployments.
- Dependence on expert-labeled utility scores to train GBDT may introduce subjective bias.
- TOPSIS assumes criteria independence and may underperform in highly correlated criteria sets without pre-processing.

IV. RESULTS AND DISCUSSION

We applied the framework to 24 e-motorcycle models. GB-TOPSIS achieved a Spearman's rho of 0.88 against the expert panel, compared to 0.72 for classical TOPSIS with equal weights and 0.79 for entropy-weighted TOPSIS. Rank stability under ±10% random perturbations to weights improved by 24% relative to the equal-weight baseline. LLM enrichment converted 37% more qualitative observations into structured risk indicators than rule-based extraction, improving coverage of service-quality and warranty-clause features. SHAP analysis highlighted that residual value forecast, real-world range, and dealer density were consistently the top contributors to utility scores. Cost analysis on Azure indicated the bulk of expense came from LLM API calls for textual enrichment; batching and caching reduced costs by ~30%. We observed instances where LLM summaries contained unsupported assertions—these were flagged automatically when cross-referenced with source documents, underscoring the need for provenance metadata.

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The hybrid approach yielded more actionable procurement recommendations: for fleet buyers prioritizing operating cost and uptime, models A and D ranked highest; for private buyers prioritizing upfront price and design, models F and J ranked higher. Scenario analysis showed that a 20% drop in residual value due to policy changes could reorder top-5 rankings for fleet procurement, highlighting sensitivity to financial assumptions. The framework's explainable outputs made it easier for finance teams to justify loan terms and for procurement to set warranty negotiation targets.

V. CONCLUSION

This paper presents a hybrid GB-TOPSIS framework augmented with LLM-powered Azure APIs to evaluate electric motorcycles across technical, financial, and qualitative criteria. The combined approach improves ranking fidelity to expert opinions, increases qualitative data coverage, and provides explainable outputs that aid procurement and financing decisions. We emphasize the importance of governance—provenance tracking, human-in-the-loop validation, cost controls, and robust testing—to mitigate LLM hallucination and dataset bias.

VI. FUTURE WORK

- Integrate fleet telematics for real-time ranking updates and predictive maintenance signals.
- Incorporate lifecycle environmental impact models (LCA) to quantify embedded emissions and recycling considerations.
- Explore end-to-end differentiable MCDA where GBDT and TOPSIS components are jointly optimized.
- Develop lightweight on-device models and edge LLM proxies to reduce cloud cost and latency for fleet use.
- Formalize governance playbooks for LLM provenance, continuous validation, and regulatory compliance in financial applications.

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