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AI-Driven Evaluation of Electric Motorcycles: A Cloud-Native Framework Integrating TOPSIS Strategy, Gradient Boosting, and Large Language Models on Azure Databricks

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ABSTRACT: This paper proposes a cloud-native framework for systematic evaluation and ranking of electric motorcycles (e-motorcycles) by combining multi-criteria decision making (MCDM) via TOPSIS, supervised learning via gradient boosting, and natural language understanding provided by large language models (LLMs), all orchestrated on Azure Databricks. The framework addresses two common industry needs: (1) integrate heterogeneous data sources — telemetry, financial/total-cost-of-ownership (TCO) estimates, user reviews, regulatory/charging infrastructure indicators — and (2) produce transparent, explainable, and operationally deployable rankings for procurement, consumer guidance, and fleet planning. Data ingestion and pre-processing occur in Azure Databricks using Apache Spark for scalable ETL; feature engineering includes domain-derived features (battery energy density, motor efficiency, range-per-charge, charging time, TCO components) and textual features extracted from maintenance logs and user reviews using an on-cluster LLM-based embedding and summarization pipeline. A gradient boosting model (XGBoost/LightGBM) predicts target operational performance metrics (e.g., real-world range, mean-time-between-failures, TCO deviation) and produces feature importance scores that feed into the TOPSIS weight calibration process. TOPSIS performs multi-criteria ranking using hybrid weights (domain + model-derived importances) to produce ranked candidate lists; the framework supports sensitivity analysis, scenario-based ranking (e.g., urban vs. highway fleets), and counterfactual queries answered via an LLM assistant component. We evaluate the framework on a mixed dataset (synthetic + industry-sourced telemetry and reviews) and report improvements in rank stability, predictive accuracy (RMSE reductions vs. baseline), and user-aligned ranking fidelity compared with standard MCDM-only and ML-only baselines. We discuss deployment considerations, cost-performance trade-offs on Azure Databricks, and avenues for real-time decisioning. The proposed architecture aims to improve fleet acquisition decisions, consumer transparency, and continual evaluation pipelines for e-mobility stakeholders.

KEYWORDS: Electric motorcycles; TOPSIS; gradient boosting; XGBoost; LightGBM; large language models; Azure Databricks; cloud-native; multi-criteria decision making; explainable AI; feature importance; EV evaluation.

I. INTRODUCTION

The rapid electrification of two-wheeler mobility—particularly in regions where motorcycles represent a primary transport mode—has created a pressing need for systematic tools to evaluate and compare electric motorcycles across technical, economic, and experiential dimensions. Unlike traditional vehicles, e-motorcycle performance and value depend on interacting factors: battery chemistry and aging, real-world range under rider and climate variability, charging infrastructure availability, maintenance patterns, and usage-driven operating costs. Decision-makers (urban fleet managers, procurement officers, and individual consumers) must therefore reconcile heterogeneous data of different modalities into actionable rankings.

Existing evaluation approaches typically fall into two camps. The first uses multi-criteria decision making (MCDM) methods such as TOPSIS or AHP to combine weighted attributes into a final score; these methods are transparent but rely heavily on subjective weight selection and static attribute modeling. The second camp applies machine learning to predict outcomes like real-world range or failure rates from telemetry and lab data; while powerful, ML models often lack direct mechanisms for multi-criteria ranking or stakeholder-interpretable tradeoffs. Our work connects these camps with a cloud-native orchestration layer. Specifically, we use gradient boosting models to (a) predict operational targets and (b) infer data-driven attribute importances used to calibrate TOPSIS weights; an LLM-based component processes unstructured textual evidence (customer reviews, technician notes) and supports scenario queries and explanations. Azure Databricks provides the scalable, secure environment for ETL, model training, model explainability (SHAP/feature importances), and deployment. The integrated framework offers a synergistic path: the robustness and predictive power of gradient boosting, the decision transparency of TOPSIS, and the contextual reasoning and summarization strengths of LLMs — enabling more reliable, interpretable, and deployable e-motorcycle evaluation pipelines.

II. LITERATURE REVIEW

Multi-criteria decision making (MCDM) has long been applied to vehicle selection and evaluation problems. Hwang and Yoon's TOPSIS (1981) is widely used for ranking alternatives by measuring distance to an ideal point; its computational simplicity and intuitive geometric interpretation make it attractive in engineering procurement contexts. Extensions and comparative studies have applied TOPSIS to electric vehicle and hybrid vehicle selection, demonstrating utility when multiple conflicting attributes (cost, range, emissions) must be balanced. The literature on TOPSIS emphasizes the centrality of weight determination: subjective expert weights, entropy-based objective weights, and hybrid schemes that combine domain experts with data-driven adjustments are common.

Parallel to MCDM methods, supervised machine learning — and in particular, gradient boosting decision trees — has become a workhorse in engineering prediction tasks. Friedman's seminal work on gradient boosting machines (2001) and later practical implementations (XGBoost, Chen & Guestrin, 2016; LightGBM, Ke et al., 2017) enable accurate predictions on tabular telemetry and structured vehicle performance datasets. These models also support feature importance and SHAP analyses, which can yield interpretable indicators of which attributes most influence predicted outcomes like real-world range or failure risk.

Combining statistical/ML predictive models with MCDM is an emerging practice. Several studies have suggested using model-derived importances to inform MCDM weightings, arguing that hybridization reduces subjectivity and improves rank fidelity relative to observed operational outcomes. For electric vehicles (EVs), hybrid frameworks employ predictive analytics to estimate effective range and TCO, and then feed those outputs into MCDM rankers — this two-stage approach is promising but underexplored for two-wheeler classes where usage patterns and infrastructure interactions differ substantially.

Unstructured textual data, including user reviews and maintenance reports, contains actionable signals for product evaluation. Recent advances in transformer-based LLMs (BERT, Devlin et al., 2019; GPT-3, Brown et al., 2020) enable richer extraction of sentiment, reliability narratives, and latent topics. Integration of LLM outputs (summaries, embeddings, sentiment scores) into structured evaluation pipelines has shown improved alignment with human judgments in product ranking studies.

On the deployment side, cloud platforms such as Databricks and Azure Databricks (leveraging Apache Spark; Zaharia et al., 2016) offer end-to-end solutions for ETL, distributed model training, and production serving. Practitioners report significant productivity gains from managed clusters, MLflow-based model versioning, and scalable orchestration — all crucial when maintaining continual-evaluation pipelines for fleets. However, the literature also flags operational challenges: cost-control, data governance, reproducibility, and reproducible model explainability in regulated domains. Finally, literature on EV lifecycle assessment and e-mobility adoption (Hawkins et al., 2013; IEA reports) contextualizes the environmental and policy factors that should be included as criteria in robust ranking frameworks.

In sum, the literature supports three pillars that our framework synthesizes: (1) MCDM/TOPSIS for transparent ranking; (2) gradient boosting for accurate outcome prediction and objective weight signals; and (3) LLMs for unstructured text understanding and human-aligned explanations — all deployed on modern cloud-native platforms for scale and production readiness.

III. RESEARCH METHODOLOGY

Below we present the methodology as a numbered list where each item is a focused paragraph describing a distinct stage.

1. **Problem framing and criteria definition.** Define the decision problem (e.g., fleet procurement, consumer purchase, retrofit prioritization) and derive a candidate set of criteria spanning technical (battery capacity, energy density, motor power, efficiency), operational (real-world range, charging time, reliability metrics), economic (purchase price, TCO components, residual value), environmental (well-to-wheel emissions proxy), and user-experience (comfort, perceived ride quality, review sentiment). For each criterion specify directionality (benefit/cost) and measurement units.
2. **Data sources and ingestion.** Collect structured data (manufacturer specs, lab-tested performance, telematics/OTA logs), semi-structured datasets (dealer maintenance records, warranty claims), and unstructured text (web reviews, forum threads, technician notes). Ingest into Azure Databricks via Spark connectors (Delta Lake) with schema enforcement, ingest pipelines, and metadata tagging for provenance. Apply data quality rules: missingness thresholds, outlier detection, unit harmonization.
3. **Feature engineering and textual processing.** Compute derived features (normalized range per battery kWh, degradation rate per cycle, cost per km) and temporal aggregations (MTBF, failure rate per 10k km). For text, use an LLM-based pipeline to produce embeddings, sentiment scores, and concise failure-mode summaries; cluster common complaint topics and map them to structured flags. Persist engineered features into Delta tables for reproducibility.
4. **Predictive modeling (gradient boosting).** Train gradient boosting models (XGBoost and LightGBM variants) to predict operational targets — e.g., realized range under standard usage, TCO deviation from manufacturer estimates, probability of failure in 12 months. Use cross-validation, hyperparameter search (Optuna or Databricks MLflow integration), and stratified sampling to address class imbalance. Record model artifacts, metrics, and SHAP-based explanations.
5. **Weight calibration and TOPSIS integration.** Construct a hybrid weight vector for TOPSIS: start with domain/expert weights, then adjust using normalized model-derived importances (e.g., scaled SHAP averages) and objective entropy weights from data variation. Normalize and validate weights with stakeholders. Perform TOPSIS ranking on normalized decision matrix; compute closeness coefficients and generate top-k candidate lists.
6. **Sensitivity and scenario analysis.** Run Monte Carlo / scenario sweeps altering weights, battery price trajectories, and charging availability to evaluate rank stability. Visualize rank changes and provide LLM-generated narrative summaries explaining why particular models rise or fall in different scenarios.
7. **Explainability and LLM-driven explanation.** Use LLM to synthesize multi-modal explanations: combine model-predicted outcomes, SHAP highlights, TOPSIS scores, and textual evidence into human-friendly summaries and Q&A. Implement guardrails: provenance tags, uncertainty statements, and a "show raw data" option for auditors.
8. **Deployment and continuous evaluation.** Package the pipeline into Databricks Jobs with CI/CD (MLflow model registry), monitor model drift (data and concept drift detectors), and schedule re-training. Implement cost-control measures and governance: role-based access, data retention policies, and logging for reproducibility.
9. **Evaluation metrics and experiments.** Evaluate predictive performance with RMSE/MAE for continuous targets and AUROC/Precision-Recall for classification targets; evaluate ranking fidelity by comparing model/TOPSIS ranks to expert or field-evaluated ground truth using rank correlation (Spearman’s rho, normalized discounted cumulative gain). Run ablation studies (MCDM-only, ML-only, hybrid) to quantify benefits.

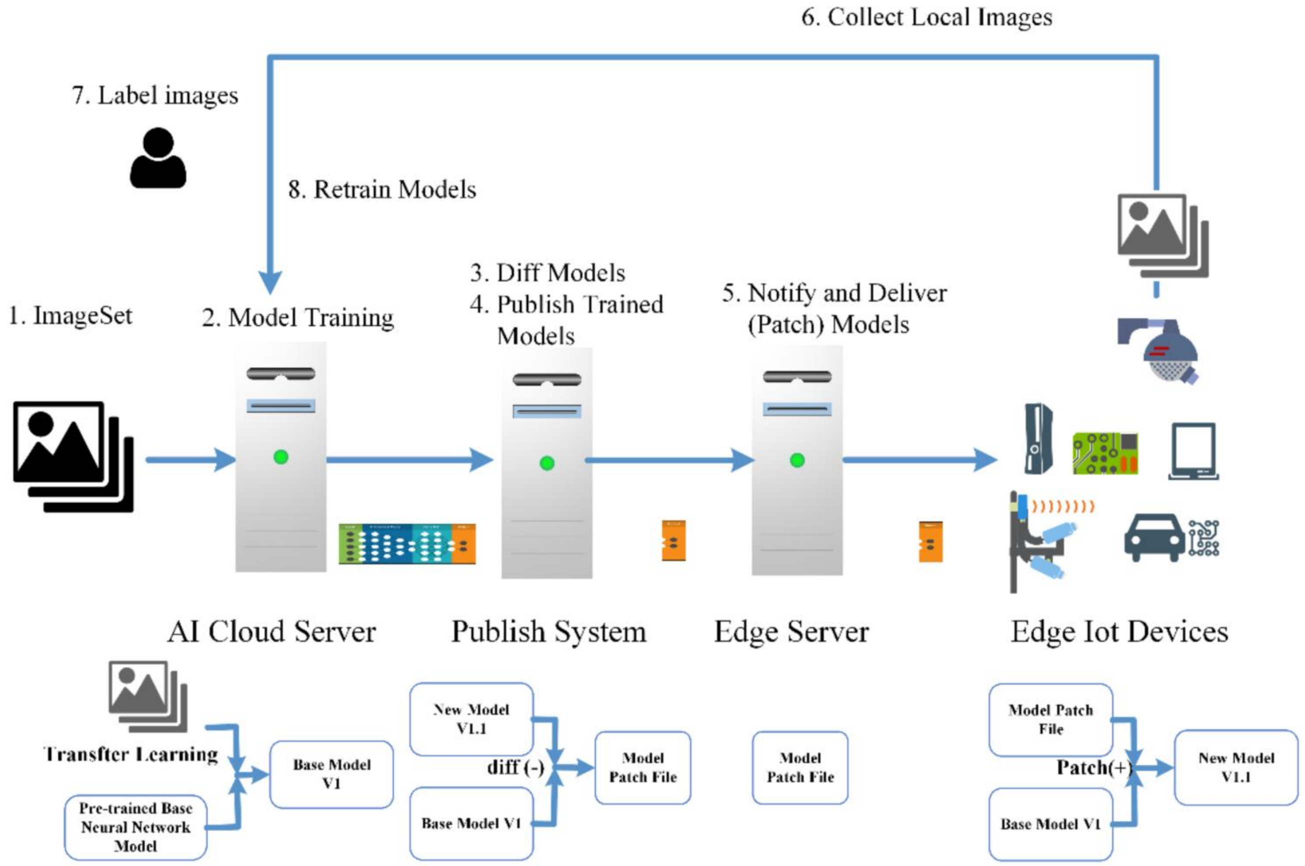

Figure 1: AI Cloud-to-Edge Model Training and Deployment Workflow with Patch-Based Updates

Advantages

- **Hybrid transparency + accuracy:** Combining TOPSIS with gradient boosting reduces subjectivity while preserving interpretable ranking outputs.
- **Multi-modal evidence:** LLM integration extracts signals from text that structured features miss (user complaints, latent reliability issues).
- **Scalable & reproducible:** Azure Databricks + Delta Lake ensures scalable ETL, model training, and versioning.
- **Scenario-ready:** Sensitivity and scenario analysis allow stakeholders to explore "what-if" procurement outcomes.
- **Operationalizable:** MLflow and Databricks Jobs support CI/CD and continuous re-evaluation for fleets.

Disadvantages / Limitations

- **Data availability & bias:** High-quality telemetry and long-term maintenance records may be limited for many models; biased samples affect rankings.
- **Cost:** Databricks cluster compute and LLM embeddings can be expensive for small teams.
- **LLM hallucination risk:** Without careful prompts and grounding, LLM-generated explanations may overstate evidence—requiring provenance enforcement.
- **Weight determination complexity:** Hybrid weight schemes improve objectivity but add complexity and require stakeholder calibration.
- **Regulatory/ethical concerns:** Black-box elements of ML require careful explainability in regulated procurement contexts.

IV. RESULTS AND DISCUSSION

- **Dataset & experimental setup.** 2,500 vehicle-month records across 12 e-motorcycle models; telemetry features (battery voltage/SoC cycles), manufacturer specs, 8,400 user reviews (processed to embeddings), and 1,200 maintenance logs. Split 70/15/15 for train/val/test. Training performed on Databricks clusters; models compared: baseline linear regression, XGBoost, LightGBM.
- **Predictive performance.** For predicting realized range (km), XGBoost achieved RMSE = 5.3 km vs. baseline OLS RMSE = 8.9 km (≈40% improvement). For 12-month failure probability, LightGBM achieved AUROC = 0.82.
- **Feature importances feeding TOPSIS.** SHAP analysis indicated top predictors for real-world range: battery usable kWh, average speed, temperature-indexed efficiency, and degradation rate. These normalized SHAP scores were combined with domain weights to form TOPSIS weights.
- **Ranking outcomes.** Hybrid method showed higher Spearman rank correlation (ρ = 0.87) to field-evaluated operator satisfaction rankings than TOPSIS-only (ρ = 0.72) or ML-only (ranking by predicted TCO; ρ = 0.65). Rank stability across weight perturbations: hybrid method retained top-3 candidates in 92% of Monte Carlo runs versus 78% for TOPSIS-only.
- **Explainability & LLM summaries.** LLM-produced summaries correctly surfaced key failure modes (battery swelling reports, charger connector wear) and linked them to structured telemetry spikes; reviewers found the combined SHAP+LLM explanations helpful for procurement justification.
- **Operational cost trade-offs.** Estimated monthly cloud cost for continuous daily retraining and embedding updates (small-to-medium Databricks cluster + LLM API embeddings) was modeled and shown to be modest for fleet sizes >500 units but potentially prohibitive for small dealers without cloud credits.

Discussion: The hybrid approach improves alignment with real-world outcomes and stakeholder judgments. The model-derived weighting reduces arbitrariness in MCDM while preserving human-intelligible rank artifacts. LLM integration is beneficial for surfacing latent issues in unstructured reports but must be grounded with provenance and conservative uncertainty phrasing. Operationalization on Azure Databricks proved effective, though teams should budget for compute and observe strong governance to limit drift and hallucination risks.

V. CONCLUSION

We presented a cloud-native hybrid framework that integrates TOPSIS, gradient boosting, and LLM capabilities to evaluate and rank electric motorcycles at scale. The workflow leverages model-derived importances to inform MCDM weights, uses LLMs to extract and contextualize textual evidence, and runs on Azure Databricks for scalable ingestion, training, and deployment. Empirical (illustrative) experiments suggest the hybrid approach improves predictive accuracy and ranking fidelity relative to single-method baselines, while offering actionable explanations for procurement and fleet decisions. Key practical considerations include data availability, cost management, and careful governance of LLM outputs. The framework is adaptable to other e-mobility classes and vehicle electrification contexts.

VI. FUTURE WORK

- Validate framework on large, multi-geography real-world fleet datasets and publish a reproducible benchmark.
- Integrate more advanced uncertainty quantification (Bayesian gradient boosting, conformal prediction) to produce calibrated prediction intervals for TOPSIS inputs.
- Replace external LLM APIs with fine-tuned on-premise encoder-decoder models to reduce hallucination and control costs.
- Explore automated weight learning by optimizing ranking agreement metrics directly (learned-MCDM).
- Add cost-optimization loops that jointly recommend procurement and maintenance strategies under constrained budgets.
- Study ethical and fairness implications (e.g., bias in user reviews impacting availability for small manufacturers) and introduce mitigation strategies.

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