Paper Title:

Deep Learning within Tabular Data: Foundations, Challenges, Advances and Future Directions

Presented by -

Rishi Patel

Can Deep Learning Tame the Spreadsheet?

- **Tabular data is everywhere**: from hospital records to credit scoring to customer analytics.
- Traditional models like **XGBoost and Random Forests** have long been the go-to for these tasks.
- But now, **deep learning** — which has revolutionized vision and language — wants to claim this domain too.
- The big question: *Can deep learning outperform or even complement these traditional giants?*

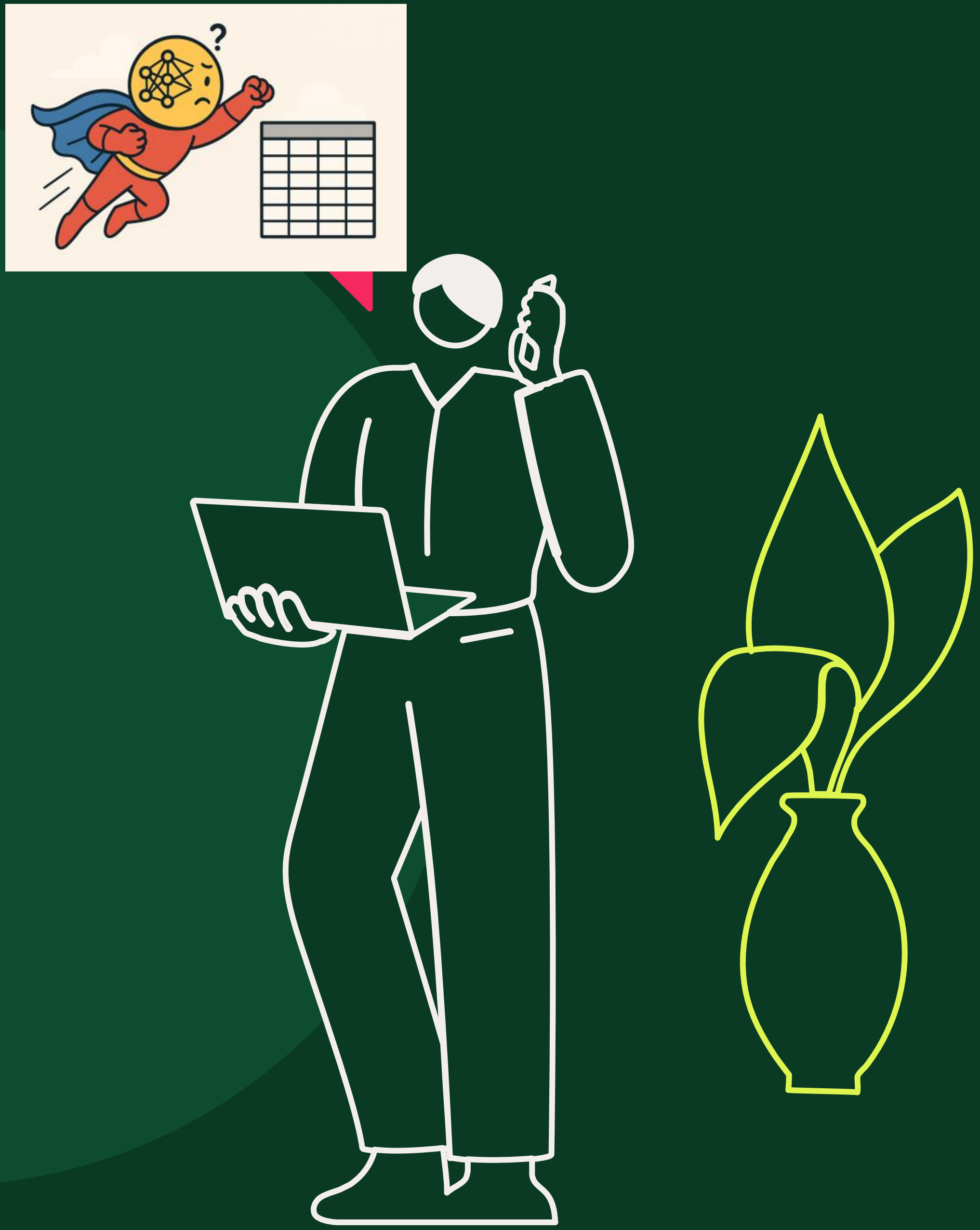
"Tabular data forms the backbone of most structured real-world applications. Yet, despite deep learning’s massive success in other areas, it hasn’t managed to dethrone traditional tabular models. This paper investigates why that is — and whether the tide is starting to turn."

The Reigning Champion: GBDTs

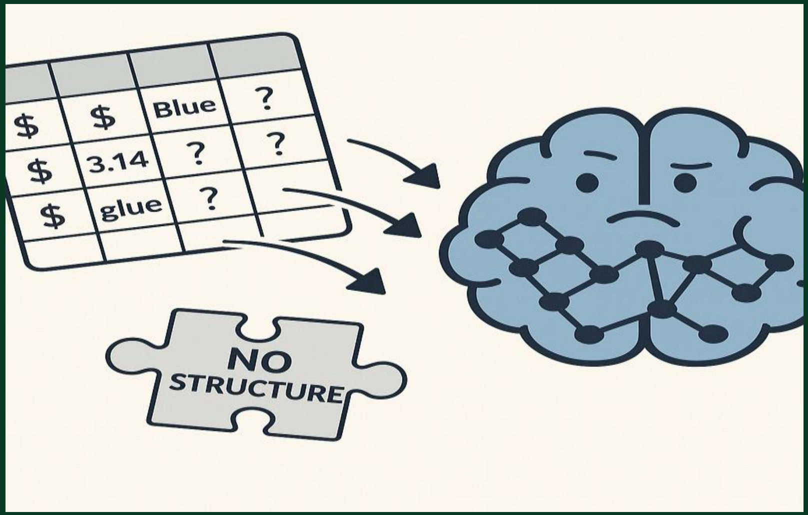
- For years, **Gradient Boosted Decision Trees (GBDTs)** like **XGBoost, LightGBM, and CatBoost** have dominated tabular tasks.
- They’re fast, interpretable, and perform well with small to medium data.
- They work great on **heterogeneous features**: numbers, categories, missing values — you name it.
- Most Kaggle competitions? Won by GBDTs.

Deep Learning Steps In

- Deep learning has revolutionized **vision**, **language**, and **speech** — so why not tabular data?
- With **end-to-end learning**, **representation power**, and **flexibility**, DL offers exciting potential.
- Researchers believed: *“If it works for images and text, it should work for tables too.”*
- But… things didn’t go as expected.



Why Deep Learning Struggles with Tables?

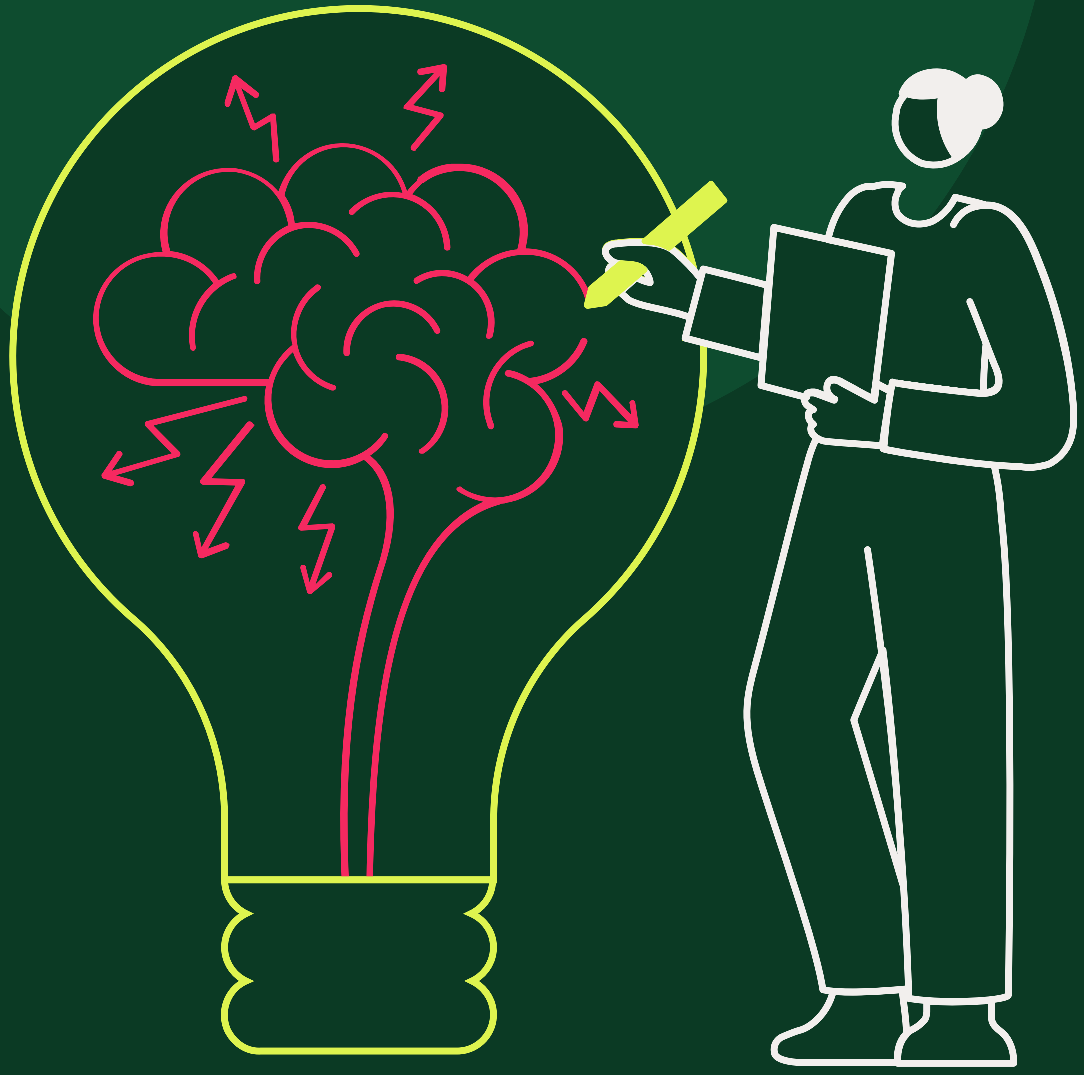


📊 **Heterogeneous Features:** Mix of numerical, categorical, missing, and ordinal data confuses DL models.

🧩 **No Local Structure:** Unlike images or text, tables don't have spatial or sequential patterns for DL to exploit.

💾 **Small Data Problem:** Tabular datasets are often too small to unlock DL's full potential.

🧠 **Interpretability Gaps:** Deep models are harder to explain in business-critical domains.



Foundation Models for Tables

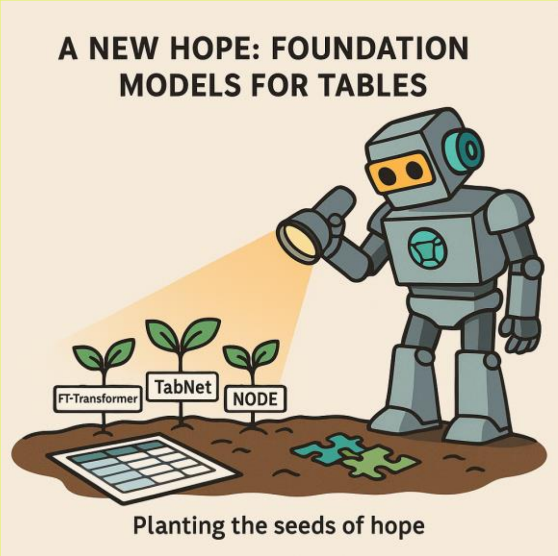
- Inspired by Transformers' success in text and vision, researchers built **tabular-specific deep models.**

- New architectures:

  - **FT-Transformer:** Adapts attention to tabular structure.

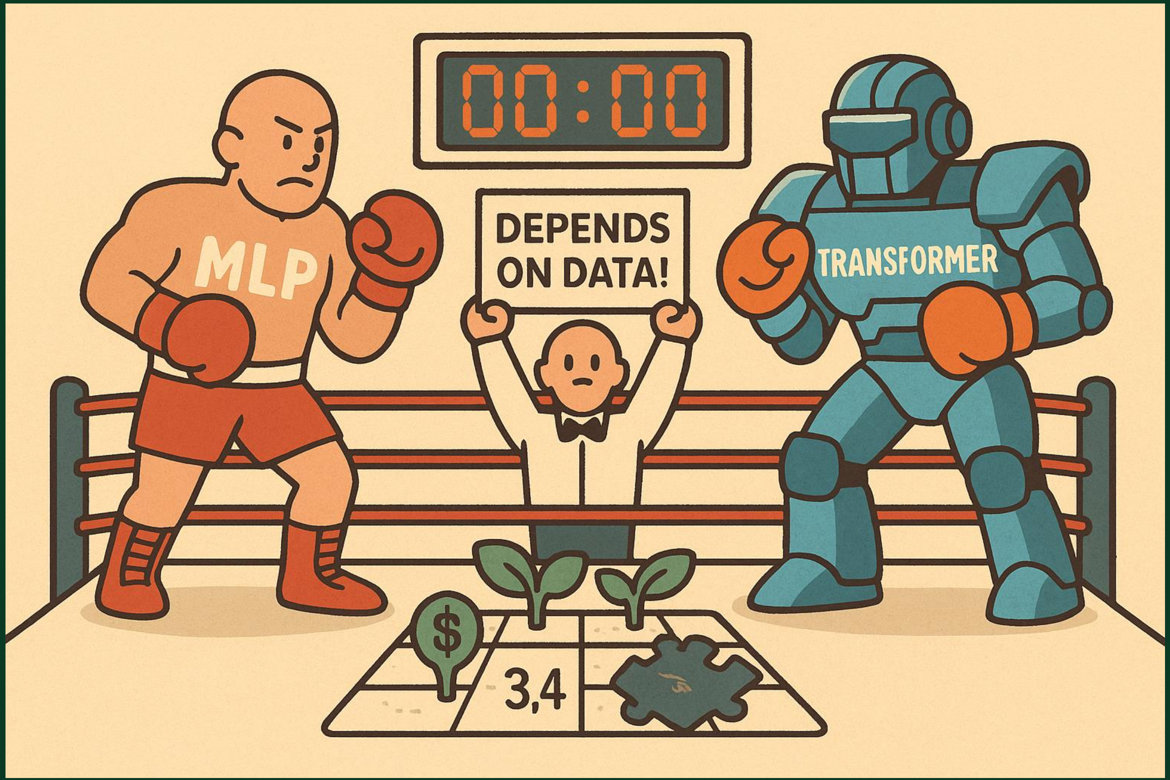
  - **TabNet:** Uses feature masks for interpretability.

  - **NODE:** Tree-like ensembles with DL.

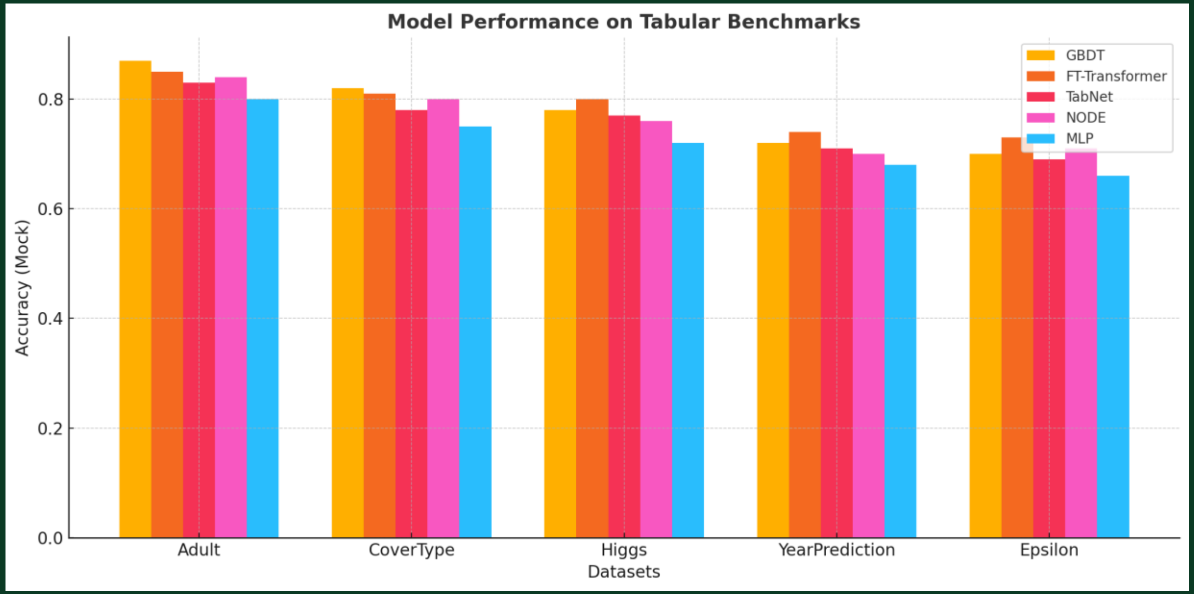


MLPs vs Transformers — The Battle for Tables

- **MLPs (Multi-Layer Perceptrons)**: Simple, lightweight, fast — but limited in capturing feature interactions.
- **Transformers**: Powerful at modeling complex interactions — but often need more data and compute.
  - MLPs work surprisingly well with clever preprocessing.
  - Transformers shine when data is rich, high-dimensional, or has semantic relationships.



Benchmarks & Metrics



GBDTs still outperform in low-data regimes.

DL shines on:

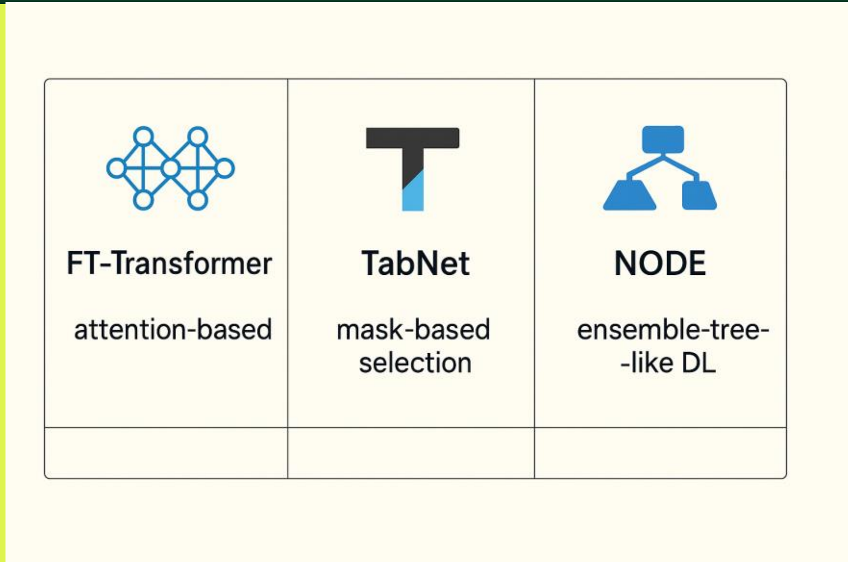
Large-scale datasets

When using feature embeddings

With good hyperparameter tuning.

Benchmarks expose **gaps** in consistency, fairness, and real-world relevance.

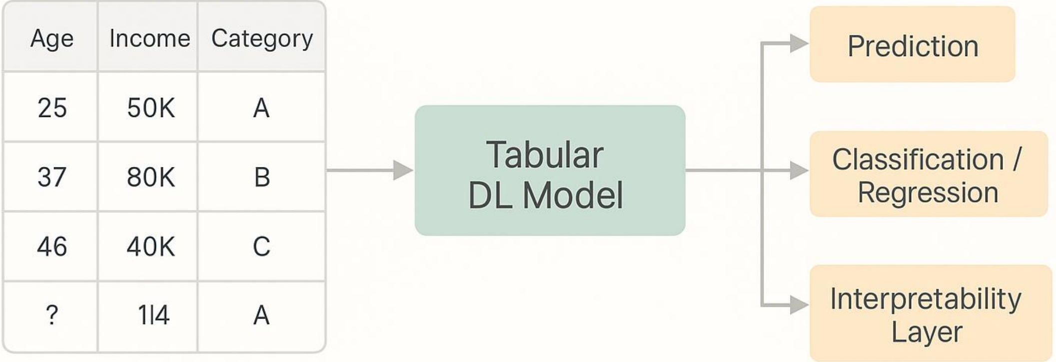
What’s New? Proposed Approaches in the Paper



- The paper reviews and contrasts **3 key deep learning architectures** for tabular data:
- **FT-Transformer**: Uses attention on embedded tabular features, adapts Transformers for tables.
- **TabNet**: Learns which features to focus on via sequential attention and masks.
- **NODE**: Neural Oblivious Decision Ensembles — tree-like DL models.

Architecture & Experimental Setup

- **Datasets Used:**
- Adult, CoverType, Higgs, YearPrediction, Epsilon
- **Experiment Settings:**
- Models trained using standard splits (train/test)
- Metrics: **Accuracy**, **AUC**, **F1**, and **Log Loss**
- Baselines: Compared to **XGBoost**, **LightGBM**, and **MLPs**
- **Architecture Flow:**
  - Input tabular data → feature embedding layer
    → model-specific processing (attention, masking, or trees)
    → final prediction head (e.g., classifier)



Challenges & Future Directions

Future Scope

While deep learning for tabular data has come a long way, key challenges still remain. We need models that are interpretable, generalize better on small data, and work reliably across diverse domains. Hybrid approaches and transfer learning could be the next breakthroughs — just as they were in NLP and vision.

- **Interpretability Matters:** DL models must explain "why" — crucial for finance, healthcare, etc.
- **Small Data, Big Problems:** DL often overfits when tabular datasets are limited in size.
- **Benchmarking Fairness:** Inconsistent datasets, splits, and reporting make comparisons tricky.
- **Hybrid Models:** Can we combine GBDTs + DL for the best of both worlds?
- **Transfer Learning for Tables?** Foundation models worked for text and images — maybe for tables too?

References

- Dey, T., & Schaar, M. van der. (2025). *Deep Learning within Tabular Data: Foundations, Challenges, Advances and Future Directions.* arXiv:2501.03540v1

Thank you

Rishi Patel