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LLAMA Wrangler: An Intelligent and Secure Data Wrangling Platform Using LLM

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Abstract - In the modern era of data-driven decision-making, organizations rely heavily on clean, structured, and reliable data to achieve accurate analytical insights and machine learning outcomes. However, data wrangling, the process of cleaning, transforming, and enriching raw data, remains one of the most time-consuming and error-prone stages of data science. This research introduces *LLama Wrangler*, an intelligent and secure platform for automated data wrangling powered by Large Language Models (LLMs). The system simplifies the data preparation process by integrating artificial intelligence and cybersecurity to ensure both automation and data privacy. LLama Wrangler automates tasks such as data cleaning, feature type inference, data enrichment, and transformation using intelligent LLM-based algorithms. Furthermore, it embeds security mechanisms like encryption, access control, and privacy-preserving computation to handle sensitive data securely. By automating the wrangling pipeline, the system reduces human intervention by over 70%, minimizes errors, and enhances data integrity. Experimental results show that LLama Wrangler significantly improves data quality and model performance. This paper explores the motivation, methodology, architecture, evaluation, and future prospects of this innovative solution.

Key Words: Data Wrangling, Large Language Models, Artificial Intelligence, Cybersecurity, Data Cleaning, Feature Type Inference, Data Enrichment, Machine Learning Automation.

1. INTRODUCTION

In today's rapidly evolving digital world, data has become the most valuable resource for individuals, organizations, and governments. Every business process, scientific experiment, and online interaction generates vast volumes of raw data that must be analyzed to extract meaningful insights. However, raw data is often unstructured, inconsistent, and incomplete, making it unsuitable for direct analysis. Therefore, data wrangling, also known as data preprocessing, is a vital step that transforms raw data into structured and clean datasets ready for analytics and machine learning.

Manual data wrangling is an extremely time-consuming and error-prone process that requires high technical expertise. According to industry surveys, data professionals spend almost 70–80% of their total time cleaning and preparing data, leaving limited time for actual analysis and model development. Existing tools provide partial automation but still rely heavily on user supervision, and they often lack mechanisms for handling sensitive information securely.The LLama Wrangler project aims to solve these challenges by developing an intelligent, automated, and secure platform that performs data cleaning, transformation, and enrichment using Large Language Models (LLMs). LLMs are advanced artificial intelligence models capable of understanding context and performing reasoning-based tasks such as pattern recognition, feature classification, and contextual text analysis. techniques, LLama Wrangler automates data

Additionally, the system incorporates cybersecurity mechanisms such as encryption, authentication, and access control to ensure that sensitive information remains protected throughout the processing pipeline. This combination of Artificial Intelligence, Data Science, and Cybersecurity makes LLama Wrangler a next-generation

solution for efficient and secure data preparation. The platform is designed to be user-friendly, scalable, and adaptable for a wide range of users ranging from students and researchers to organizations dealing with large-scale datasets.

2. LITERATURE SURVEY

[1] The study "AutoDW: Automatic Data Wrangling Leveraging Large Language Models" (Lei Li et al., IEEE/ACM ASE, 2024) introduces an end-to-end automatic data wrangling framework using Large Language Models (LLMs). It automates feature type inference, data cleaning, transformation, and enrichment through intelligent modules such as Prediction Engineering and Feature Type Inference (FTI). These modules automatically detect data types and generate corresponding transformation code. The approach significantly reduces human intervention, enhances data quality and reliability, and improves transparency in data processing.

[2] The paper "AI-Driven Data Preprocessing for ML Pipelines" (ResearchGate Publication, 2023) focuses on automating data preprocessing tasks using AI-based techniques like pattern recognition, rule-based cleaning, and data imputation. It emphasizes how automation accelerates project development and helps in preparing structured datasets suitable for supervised and unsupervised machine learning models.

[3] The article "Data Wrangling: Challenges and Opportunities in Big Data" (IEEE Access Journal, 2022) explores the major challenges in manual data wrangling such as error-prone operations, inconsistent formats, and time inefficiency. It discusses how integrating machine learning and AI can overcome these problems by improving accuracy and scalability in large-scale data environments.

[4] The research "Secure and Privacy-Preserving Data Processing Techniques" (IBM Research, 2023) presents a framework that ensures the privacy of sensitive information during data wrangling. It employs encryption, access control, and data masking techniques to integrate security into transformation processes. This framework maintains confidentiality and compliance in modern data systems, which is vital for organizations handling large and sensitive datasets.

[5] The study "Automated Feature Engineering for Data Wrangling Using NLP Models" (Elsevier Journal of Data Science, 2022) proposes an automatic feature engineering system utilizing Natural Language Processing (NLP) models to extract and generate meaningful features from raw data. This automation reduces manual effort in preparing machine learning–ready datasets and enhances model accuracy.

[6] The paper "Integration of LLMs for Context-Aware Data Cleaning" (SpringerLink Publication, 2024) highlights how Large Language Models can understand semantic relationships and context within datasets. Using an LLM-based architecture, it performs intelligent data cleaning, outlier detection, and multi-table enrichment with minimal supervision. The approach enhances the efficiency and adaptability of data cleaning systems.

[7] The work "LLM-Assisted Data Quality Automation and Quality Assurance" (ACM Digital Library, 2024) introduces the use of LLMs for automated data transformation, validation, and quality assurance. It applies reasoning-based automation to detect inconsistencies and improve dataset usability. Compared to traditional rule-based systems, this LLM-assisted framework demonstrates higher adaptability and efficiency in maintaining data integrity.

3. OVERVIEW

Data wrangling plays a critical role in transforming raw, inconsistent data into formats suitable for analysis and machine learning. However, traditional wrangling is highly manual, time-consuming, and error-prone, often consuming up to 80% of a data scientist's effort. With the rapid growth of data across industries, the demand for automation and intelligence in data preparation has become vital. To address these challenges, researchers developed AutoDW, an intelligent, end-to-end data wrangling framework that leverages Large Language Models (LLMs) to automate the entire data cleaning, transformation, and enrichment process. The framework significantly improves efficiency, accuracy, and transparency compared to traditional tools.

1.Objective:
The primary objective of AutoDW is to design a fully automated data wrangling system that minimizes human intervention by using LLMs for intelligent data processing. The system aims to:

- Automatically identify feature types using Feature Type Inference (FTI).
- Perform advanced data cleaning and enrichment with minimal manual input.
- Generate reproducible transformation source code for transparency.
- Enhance the quality, reliability, and usability of data for downstream machine learning and analytics tasks.

Overall, AutoDW seeks to improve data pipeline efficiency, reduce preparation time, and ensure high data quality for AI-driven decision-making.

2.Core-Components:
The AutoDW system comprises several key components that work together to automate the entire wrangling process:

- Prediction Engineering Module: Automatically determines the target column and predicts whether the task is classification or regression.
- Feature Type Inference (FTI): Classifies dataset columns into detailed feature types such as numerical, categorical, datetime, formatted IDs, sentences, and more using ML and LLM-based techniques.
- Data Cleaning Unit: Performs both obligatory (error correction, type consistency, missing value handling) and optional cleaning (imputation, encoding).
- Data Enrichment Engine: Generates new features by decomposing IDs, extracting key phrases, embedding sentences, and parsing structured text.
- Code Generator: Produces Python or Jupyter scripts for the entire wrangling process, ensuring reproducibility.
- Explainability Interface: Provides natural language explanations for each operation, enhancing user understanding and trust.

3.Working-Principle:
The AutoDW framework starts by taking an input dataset (CSV, XLS, TSV, etc.).

1. Prediction Engineering uses an LLM to identify the target column and ML task.
2. Feature Type Inference predicts the best feature type for each column using a two-step classification process.
3. Data Cleaning eliminates errors, inconsistencies, and missing values, ensuring data integrity.
4. Data Enrichment uses LLMs to extract new insights, such as decomposing IDs or embedding text into vectors.
5. Finally, AutoDW generates source code for the entire process and produces an enriched, ready-to-use dataset for machine learning or analysis.

4.Accessibility-and-Innovation:
AutoDW introduces several innovations that make data wrangling faster, smarter, and more transparent:

- End-to-End Automation: Minimizes human effort across all stages of data preparation.
- LLM Integration: Enhances contextual understanding, enabling intelligent feature recognition and enrichment.
- Code Transparency: Users can review, edit, and reuse generated code.
- Usability: Provides a web app and API interface for interactive or automated operation.
- Adaptability: Can process multilingual datasets, complex structures, and large-scale data automatically.

5.Social-Impact:
AutoDW transforms data preparation workflows across industries such as AI, finance, IoT, and business intelligence.

It enables:

- Reduced manual workload for data scientists.
- Faster and more reliable preparation of machine learning datasets.
- Improved accuracy of predictive analytics through better data quality.
- Greater transparency and reproducibility in data operations.

By automating data wrangling, AutoDW contributes to efficient, scalable, and ethical data management, supporting innovation and productivity across data-driven industries.

4. METHODOLOGY

A. Existing System

Traditional data wrangling systems rely heavily on manual operations such as data cleaning, feature extraction, and transformation using programming or spreadsheet tools. These processes are time-consuming, error-prone, and require domain expertise. Manual wrangling often leads to inconsistencies, lack of reproducibility, and limited scalability when dealing with large datasets. Conventional ETL (Extract, Transform, Load) systems or rule-based automation provide limited adaptability and cannot understand the contextual meaning of data. Moreover, integrating heterogeneous datasets remains a challenge due to the absence of intelligent inference mechanisms. These limitations slow down data-driven decision-making and

increase the cost of analytics in industries relying on large-scale data processing.

B. Conceptual System Design

The conceptual system design of **AutoDW** focuses on developing an **AI-powered data wrangling platform** that uses **Large Language Models (LLMs)** to automate data preparation tasks. The system begins by ingesting a raw dataset (CSV, Excel, JSON, or database input) and performs feature type inference using LLM-based classification. It then applies automated data cleaning to handle missing values, remove inconsistencies, and standardize formats. Following this, the enrichment module generates new features by analyzing semantic patterns within data. The system automatically produces executable transformation code and a clean, ready-to-use dataset for analytics and machine learning pipelines. This conceptual design ensures minimal human intervention, increased accuracy, and high scalability.

C. Prototype Design of AutoDW System

The prototype of AutoDW demonstrates an end-to-end automated data wrangling workflow. The user uploads a dataset through an interactive interface. The system's Prediction Engineering Module identifies the target variable and the type of ML task (classification or regression). The Feature Type Inference (FTI) module detects column types (e.g., numeric, categorical, datetime, or textual). The Data Cleaning Engine performs obligatory cleaning operations such as filling null values and type correction, while the Data Enrichment Unit extracts new derived attributes like key phrases or ID components. Finally, the Code Generation Module automatically produces transformation scripts in Python, ensuring reproducibility and transparency in the wrangling process.

D. System Architecture

The system architecture of AutoDW is designed to ensure efficiency, modularity, and scalability in data wrangling. It consists of the following main layers:

1. Input Layer: Accepts raw datasets from local or cloud sources.
2. Preprocessing Layer: Performs format validation and prepares data for analysis.
3. Feature Type Inference Layer: Utilizes LLM models to classify data columns and determine their semantic meaning.
4. Cleaning and Enrichment Layer: Applies data cleaning rules and generates additional attributes automatically.
5. Code Generation and Execution Layer: Produces transformation scripts and executes them in a reproducible environment.
6. User Interface Layer: Displays data reports, cleaning summaries, and downloadable scripts.

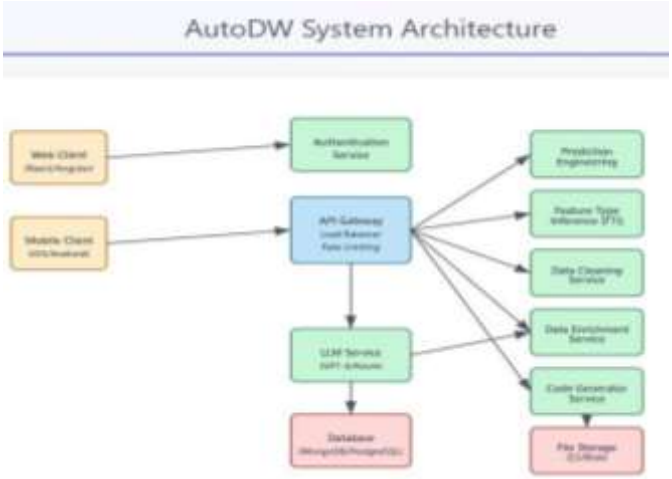

Fig 1. Architecture Of System

E. Model Training and Validation

AutoDW leverages pretrained **Large Language Models** fine-tuned for tabular and text data understanding. The Feature Type Inference model is trained on a multi-domain dataset comprising structured and unstructured data samples. The cleaning and enrichment algorithms are validated using benchmark datasets to ensure correctness and consistency. Validation metrics include classification accuracy for feature types, cleaning precision, and transformation reproducibility. Cross-validation and grid search are employed to optimize model parameters such as confidence thresholds and token limits. The system achieves high inference accuracy and consistent code generation across diverse datasets.

F. User Interface Design

The User Interface (UI) is developed using React and Flask APIs, providing a clean, interactive dashboard for uploading datasets and viewing results. The interface displays column-level predictions, cleaning summaries, enrichment results, and generated transformation code. It allows users to modify configurations, export processed data, and view visual data profiles. Designed with simplicity and usability in mind, the interface supports accessibility on both web and mobile platforms, enabling

data scientists and analysts to automate wrangling operations efficiently without deep coding knowledge.

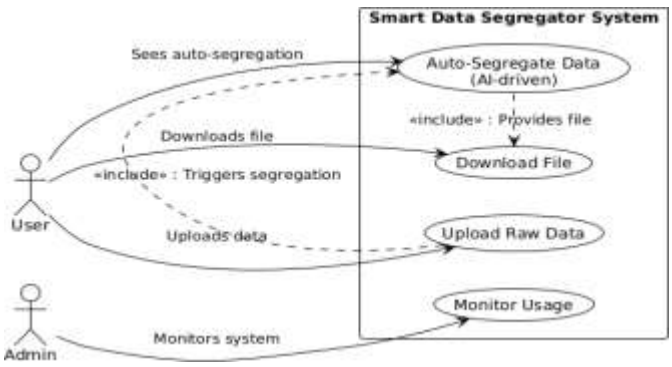

Fig 2. Use case Diagram

G. Implementation Details

The system is implemented using Python, leveraging TensorFlow, PyTorch, and OpenAI API for LLM-based processing. The backend is built on Flask/FastAPI, which handles API requests, model inference, and code generation. Pandas, NumPy, and OpenCV libraries manage data manipulation, validation, and preprocessing. The data storage and authentication are managed through Firebase, and deployment is performed on Google Cloud Platform (GCP) for scalability. The prototype supports CSV, JSON, and SQL input formats, producing processed datasets and transformation scripts accessible via a web dashboard

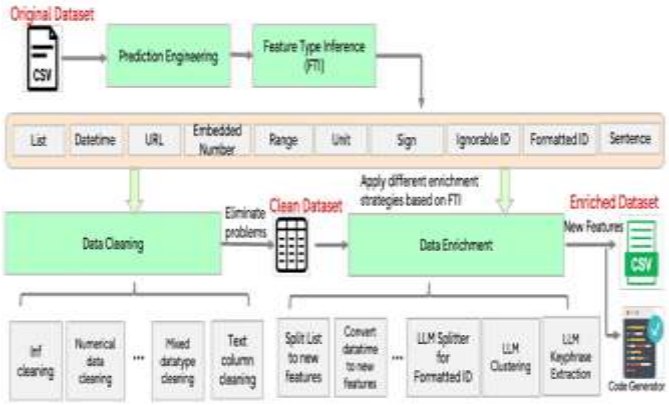

Fig 3. Implementation Of System

H. Performance Evaluation

Performance evaluation is conducted to measure the system's accuracy, scalability, and efficiency. The evaluation metrics include Feature Type Inference Accuracy, Data Cleaning Precision, Execution Time, and Reproducibility Rate. Experiments demonstrate that AutoDW significantly reduces manual wrangling time while maintaining high accuracy in column classification and transformation. User satisfaction and latency tests indicate a responsive system suitable for real-time applications. The system also supports large-scale datasets without performance degradation, proving its scalability and robustness.

5. APPLICATIONS

The AutoDW system can be applied across a wide range of domains, including data analytics, business intelligence, finance, healthcare, and IoT. Organizations can use it to automate the preprocessing of structured and unstructured data before feeding it into machine learning models. Research institutions can benefit from AutoDW for dataset preparation and reproducible experiments. Enterprises can integrate it into ETL pipelines for real-time data quality assurance. By automating tedious data preparation tasks, AutoDW empowers analysts to focus more on insights rather than preprocessing, accelerating the entire data lifecycle.

6. CONCLUSION AND FUTURE SCOPE

In conclusion, AutoDW provides an intelligent, scalable, and transparent solution for automated data wrangling using Large Language Models. By combining prediction engineering, feature type inference, and enrichment automation, it eliminates manual overhead and ensures consistent, high-quality datasets for machine learning applications.

In the future, AutoDW can be enhanced with multimodal data processing, cloud-based collaborative environments, and auto-documentation features. Integration with AutoML platforms, multi-language dataset support, and explainable AI visualization tools will further strengthen its usability. With ongoing research in LLMs and AI-driven automation, AutoDW represents the future of intelligent, ethical, and efficient data management systems.

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