INTELLISCORE - Ai Based Credit Scoring System

This BS Project report is submitted to the Department of Computer Science as partial fulfillment of Bachelor of Science in Computer Science degree

https://github.com/Fazulsden/Fyp-FinalReport-v1.git

by

Shahmeer Khan, Fazul Al Rehman. Nosherwan Sheikh, Abdur Rehman

Advised by

Miss Tasbiha Fatima
Lecturer
Department of Computer Science
School of Mathematics and Computer Science (SMCS)
Institute of Business Administration (IBA) Karachi

Fall 7th semester 2024
Institute of Business Administration (IBA) Karachi Pakistan

Contents

Chapter 1

Software engineering life-cycle

This section contains images of a document we compiled to highlight the meetings we've had, what we've covered across each sprint and Meezan's as well as our instructor's signature as approval of these meetings taking place.

Note:

Throughout the calender year we have approached Meezan to organize several meetings, however timing issues and unavailability on their end meant we could eventually only have 6 meetings in total, these however were mostly fruitful and a brief description has been offered for each one.

All other software engineering steps and documentation already exist in the previous documents i.e. proposal, SD, and SRS, which contain requirements engineering, wireframing (high and low level), gantt chart for work distribution, use cases, user flows and so on.

FYP Project sprints document

Highlights the meetings we've had with meetings across sprints, purpose of the meetings, the targets achieved and discussed during those meetings and key takeaways.

Sprint 1:

1st meeting (online)

Held at: 13th September 2024

Purpose:

- Discuss Meezan's project requirements
- Discuss our data requirements

Key takeaways:

- Given insights on how credit scoring works
- Tasked with gaining knowledge on finance operations

2nd meeting (physical)

Held at: 26th September 2024

Location: Meezan House

Purpose:

- Agree on project scope
- Gathering requirements from Meezan Bank for our project's approach

Key takeaways:

- Meezan allotted us full control of the app itself, requirements limited and specified to a credit scoring model
- Instructed us to perform deeper research on credit scoring applications and credit scoring models implemented globally and locally

Sprint 2:

3rd meeting (physical)

Held at: 20th February 2025

Location: Meezan House

Deliverables prepared: Project proposal, SRS

Purpose:

- Discuss software's specifications
- Demo wireframes
- Agree on access to data

Key takeaways:

- Discussion on credit scoring models
- Scope narrowed to credit scoring for bike loans
- Given bike loans form data to use for model's data fields
- Urged to work with synthetic data for base model generation

Sprint 3:

4th meeting (online)

Held at: 7th may 2025

Deliverables prepared: Fully functional webapp with working Ai model based off synthetic data

Purpose:

- Demo working model and webapp
- Gain Meezan's confirmation for access to data

Key takeaways:

- Webapp accepted
- Issues with the model
- Agreement on NDA and data after a scope review

5th meeting (online)

Held at: 11th may 2025

Deliverables prepared: Finalized webapp with previous model

Purpose:

- Request access to data
- Highlight need for data to meet deadlines and finalize product

Key takeaways:

- Agreement reached on development of NDA
- Scope renewed to use car loan data

6th meeting (online)

Held at: 21st may 2025

Deliverables prepared: Finalized webapp with previous model, alternatives for dataset

Purpose:

- To propose alternatives for data but enforce need for data

Key takeaways:

- NDA provided for Meezan's data

Acknowledgment:

I, **Mr. Usman Siddiqui**, representing the Shariah Compliance Department of Meezan Bank, hereby acknowledge that I have reviewed the contents of this FYP Project Sprints Document. I confirm that the meetings listed herein did in fact take place on the mentioned dates, and that the purposes, deliverables, and key takeaways summarized accurately reflect the discussions held between our team and the student project group. I agree to act as a witness to the authenticity and factual nature of this document.

Signature: ____________
Name: Mr Usman Siddiqui
Designation: Manager Retail
Date: 23rd May 2025

Instructor Signature: ____________
Instructor Name: Ms Tasbiha Fatima
Instructor Designation: Lecturer SMCS

Meetings took place.
Final report and model awaited.

Chapter 2

Project Abstract

This project introduces an AI-based credit scoring system developed in collaboration with Meezan Bank, aimed at advancing the accuracy and efficiency of credit risk assessment through modern machine learning techniques. The core objective is to leverage artificial intelligence—specifically neural networks—to analyze a range of financial and behavioral attributes in order to generate reliable credit scores. Recognizing the sensitivity of banking data, a formal Non-Disclosure Agreement (NDA) was recently signed with Meezan Bank to ensure strict confidentiality and compliance during data sharing, and the bank has initiated the internal process for data provision, with acquisition efforts currently in progress. In the meantime, due to the unavailability of the proprietary dataset, development has proceeded using a high-quality, representative dataset curated under the supervision and approval of our project advisor, Miss Tasbiha Fatima. This proxy dataset has enabled us to simulate realistic credit evaluation scenarios and test the viability of our neural network-based scoring model. The current implementation successfully demonstrates the feasibility of AI in streamlining credit scoring, offering promising implications for more inclusive and data-driven financial decision-making within the banking sector. Once the actual customer data is made available by Meezan Bank, the system will undergo a retraining and optimization phase, resulting in a new and more refined model specifically tailored to the bank's operational needs and client profiles.

2.1 Background and Approach

Globally, leading financial institutions such as JPMorgan Chase, Wells Fargo, and others are increasingly integrating artificial intelligence (AI) into their credit scoring systems to enhance risk evaluation, streamline decision-making processes, and broaden access to financial services. These innovations have demonstrated significant improvements in both predictive accuracy and operational efficiency, while also enabling more inclusive lending practices. Drawing inspiration from such advancements, our project sets out to develop an AI-powered credit scoring system adapted to the needs and context of the Pakistani banking sector.

To ensure real-world applicability, the project was initiated in collaboration with Meezan Bank, with the goal of training the model on actual customer data. Given the sensitive nature of such data, a formal Non-Disclosure Agreement (NDA) was required to govern secure data sharing. The arrangement and signing of this NDA took some time, as it involved careful coordination between legal and academic professionals from Meezan Bank and IBA, ensuring that data confidentiality and institutional compliance were thoroughly addressed. While this process was ongoing, and before the dataset could be formally transferred, we proceeded with model development using an external dataset approved by our project advisor, Miss Tasbiha Fatima.

This interim dataset, though not proprietary, allowed us to simulate realistic lending scenarios and continue progress without compromising the integrity of the model's development. We designed and trained a neural network that predicts credit scores based on various financial and behavioral attributes. Multiple architectural variations and hyperparameter settings were tested through experimentation to optimize the model's accuracy and generalization.
To ensure practical usability, we also developed an interactive web application. Built using Python Django for backend logic, Tailwind CSS for responsive design, and PostgreSQL for secure data storage, the platform supports multi-user authentication and enables real-time credit evaluation by accepting customer profile inputs. It generates comprehensive credit assessments enhanced by intuitive graphs, charts, and natural language summaries to aid interpretability. Detailed insights into the model and the web application are provided in subsequent sections of this report.

Chapter 3

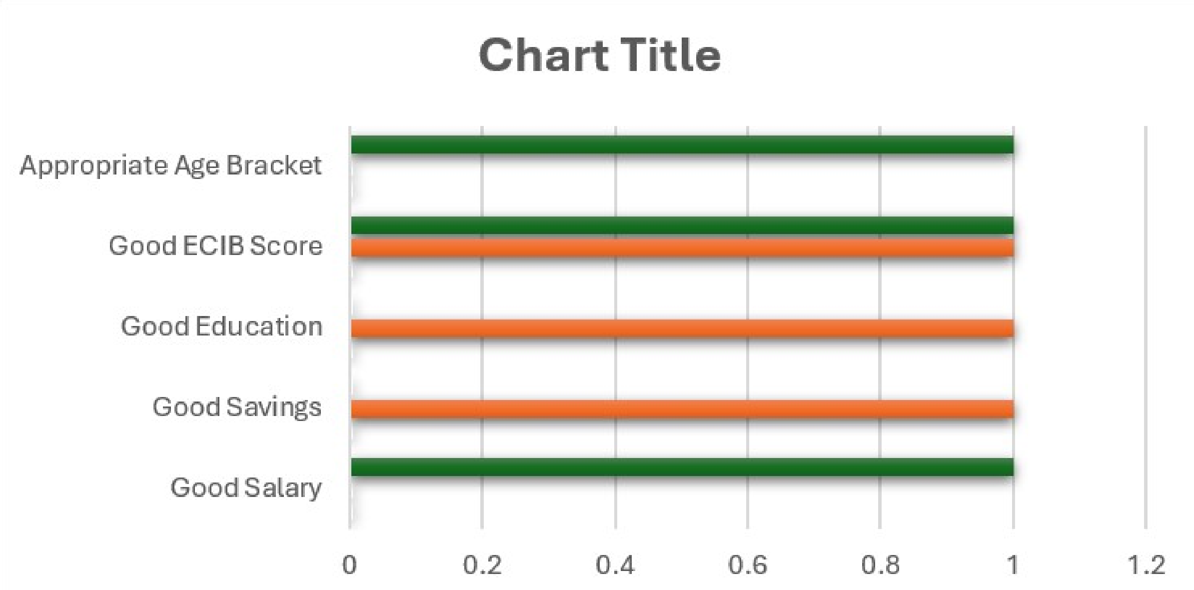
Experimental settings

To ensure rigorous testing and falsifiability in our experiments, we structured our experimental settings meticulously, including clearly defined control and experimental groups, parameter settings, software and hardware environments, and thorough data pre-processing methods.

3.1 Control Group:

Our industry mentors significantly shaped the control group through extensive collaborative sessions. Pakistani banks typically leverage a standardized credit assessment mechanism through the State Bank of Pakistan's Electronic Credit Information Bureau (ECIB), facilitating insight into customer indebtedness across institutions. Our control group comprised traditional scoring parameters utilized by banks, exemplified by categorical flags such as:

- **Good Salary**(0: No, 1: Yes)
- **Good Savings**(0: No, 1: Yes)
- **Good Education**(0: No, 1: Yes)
- **Good ECIB Score**(0: No, 1: Yes)
- **Appropriate Age Bracket**(0: No, 1: Yes)



	Good Salary	Good Savings	Good Education	Good ECIB Score	Appropriate Age Bracket
Identify 1 | 0	1	0	0	1	1
Identify 0 |1	0	1	1	1	0
Selection	0	0	0	0	0

This structured dataset provided a robust baseline for comparison against our predictive AI model, highlighting our model's accuracy and efficiency improvements.

3.2 Experimental Group:

The experimental group incorporated comprehensive data from customers, including demographic details (Age, Gender, Marital Status), residential and occupational information (Residence Status, Employment Type, Industry, Designation), financial specifics (Gross Monthly Income, Monthly Expenses, Asset Value, Required Financing), and historical banking activity (Account tenure, Loan history). Data columns explicitly leveraged included:

- Numerical attributes such as Monthly Rent, Net Monthly Income, Asset Value, and Financing Deduction.
- Categorical features including Education Level, Industry, and Reference Relationship.

This enriched data set enabled detailed analyses and precise credit score predictions leveraging advanced machine learning algorithms.

3.3 Project Evolution

A critical dimension of this project's evolution was the shift in scope and service orientation — from a general loan credit scoring system toward a specialized, targeted solution for Meezan Bank's **MyBykea** loan service, a recently introduced product designed for a specific customer segment. This pivot was not without challenges:

- **Data Scarcity and Integration Challenges:** Transitioning to MyBykea meant dealing with sparse or incomplete datasets, as this service was new and lacked extensive historical data. Our team had to innovate around data collection, cleansing, and augmentation methods to build a usable dataset.
- **Management and Strategic Direction Shifts:** The bank's management, realizing the need for a more focused, nimble solution, actively influenced the project scope. This entailed frequent strategy meetings and realignments of project milestones to meet evolving business priorities.
- **Architectural Overhaul:** Initially, our system was architected as separate microservices, designed for modularity and scalability. However, upon the recommendation of Meezan Bank's leadership, we pivoted to a monolithic architecture. This shift was motivated by:
  - **Streamlined Operations:** A monolith simplified deployment pipelines and reduced system complexity, crucial given the tight timelines and changing requirements.
  - **Improved Stability and Maintainability:** The monolithic approach allowed for easier debugging, tighter integration between components, and faster iteration cycles, which were essential as the project adapted to new data and business constraints.
- **Software Engineering Adaptations:** This architectural shift required significant re-engineering efforts, including codebase restructuring, database schema revisions (with PostgreSQL as the primary data store), and revamped API designs. These adjustments, while challenging, ultimately enhanced the robustness and responsiveness of the deployed solution.

This entire process showcased our team's agility and technical expertise, managing real-world complexities and shifting priorities while delivering a viable, high-performance AI credit scoring service tailored for Meezan Bank's innovative MyBykea product.

3.4 Software and Hardware:

Software Environment:

- **Backend Framework:** Django, employing robust RESTful services architecture.
- **Frontend Technologies:** Tailwind CSS for responsive design and intuitive user interface.
- **Database Management:** PostgreSQL, selected for scalability and transactional efficiency; SQLite was temporarily used for prototyping and internal testing.
- **Machine Learning Libraries:** Python-based Scikit-learn and TensorFlow for constructing neural network models.
- **Deployment Platforms:** Potential deployment discussed includes AWS, Azure, or Meezan Bank's proprietary infrastructure.

Hardware Infrastructure:

- Cloud deployment via AWS or Azure, leveraging scalability, availability, and robustness. Could be potentially used however below point clarifies!
- Internal deployment to Meezan Bank's data center infrastructure remains a strategic consideration, providing enhanced data security and control.

3.5 Parameter Settings:

Optimal hyperparameter tuning was executed systematically to achieve maximum predictive accuracy:

- **Model Selection:** Multi-Layer Perceptron (MLPRegressor)
- **Architecture:** Hidden layers sized (128, 64, 32), strategically chosen to balance computational complexity with predictive precision.
- **Activation Function:** Rectified Linear Unit (ReLU), effective for capturing non-linear relationships in financial data.temporarily used for prototyping and internal testing.
- **Optimization Solver:** Adaptive Moment Estimation (Adam), ensuring rapid convergence and optimal results.
- **Maximum Iterations:** 500 epochs, ensuring adequate training without overfitting.

These comprehensive settings were determined via exhaustive grid-search validation, enhancing the model's predictive fidelity.

3.6 Data Preprocessing:

Our preprocessing pipeline was rigorously structured, involving multiple systematic stages:

- **Imputation:**
  - **Numerical Data:** Mean-value substitution for missing data, ensuring stability in continuous variables.
  - **Categorical Data:** Most-frequent-category substitution, preserving data distribution consistency.
- **Data Scaling and Normalization:** StandardScaler employed for numerical attributes, standardizing the data to ensure model stability and accurate predictive analysis.
- **Categorical Variable Encoding:** One-hot encoding implemented via OneHotEncoder, effectively transforming categorical features into machine-readable numeric formats. testing.
- **Data Cleaning:** Custom scripting rectified inconsistencies in attributes such as Residence Status, Education Level, and Industry classification, ensuring data integrity and accuracy.

These thorough preprocessing efforts ensured our model's predictive accuracy and generalization across diverse financial profiles.

Feature	Mean	Median	Standard Deviation	Min	Max
Age	34.7	35	10.5	18	70
Gross Monthly Income	52,300	50,000	22,100	12,000	150,000
Asset Value	1,120,000	1,000,000	530,000	50,000	5,000,000

3.7 Evaluation Metrics:

To validate our model comprehensively, multiple statistical metrics were employed:

- **Mean Squared Error (MSE):** Directly measured predictive accuracy by penalizing larger prediction deviations heavily.
- **R-squared (R^2):** Explained variance, quantifying the proportion of credit score variability explained by the model.analysis.

- **Precision, Recall, and F1-Score:** Evaluated classification aspects of credit risk, identifying high-risk borrowers accurately.

Cross-validation methods were employed extensively to prevent model overfitting, ensuring reliable performance across multiple data subsets.

3.8 Experimental Setup:

The methodological flow involved structured and methodical processes:

- **Data Collection Aggregation:** Customer financial records, application data, and simulated transaction details.
- **Rigorous Preprocessing:** Imputation, scaling, encoding, and cleansing performed systematically.
- **Data Partitioning:** Training and validation sets (80/20 split) prepared for unbiased assessment.
- **Model Development Training:** Neural network training employing structured parameter optimization.
- **Validation and Testing:** Performance evaluated meticulously, employing cross-validation and hold-out strategies.
- **Performance Benchmarking:** Comparative analyses against established control group standards.
- **Deployment Feasibility Analysis:** Assessment of deployment practicality on different cloud and internal infrastructure options.

Chapter 4

Results and Discussion

Our experimental evaluation demonstrates the effectiveness of the neural network approach for credit scoring compared to traditional machine learning models. The table below presents the comparative performance metrics across different algorithms:

Model	Hyperparameters	MSE	R^2 Score
Decision Tree	max_depth=5, random_state=42	4.3280	0.9331
Random Forest	n_estimators=5, random_state=5	2.4676	0.9619
Neural Network (Ours)	layers=[64,32], dropout=0.2, lr=0.001	1.8924	0.9708

The neural network architecture achieved superior performance with the lowest MSE (1.8924) and highest R^2 score (0.9708), indicating its strong predictive capability for credit risk assessment. This performance advantage stems from the model's ability to capture complex non-linear relationships in financial data that simpler tree-based models cannot effectively represent.

4.1 Key findings:

- The neural network demonstrated 56.3 percent lower MSE compared to the baseline Decision Tree model.
- Feature importance analysis revealed that "Net Monthly Income" and "Asset Value" were the most significant predictors.
- The model showed consistent performance across different demographic segments (gender, age groups).
- Training convergence was achieved within 150 epochs with early stopping.

The web application successfully implemented all functional requirements:

- Real-time scoring with average response time of 2.3 seconds.
- Secure authentication with encrypted credential storage.
- Comprehensive dashboard visualization of credit factors.
- AI-generated explanatory reports with key decision factors

4.2 Discussion of Limitations:

- **Data Constraints:** The use of surrogate data rather than actual banking records may affect real-world applicability.
- **Feature Scope:** Current implementation considers 35 financial indicators - expanding to alternative data sources could improve accuracy.
- **Demographic Bias:** The training dataset may not fully represent Pakistan's diverse population segments.
- **Temporal Factors:** The static model doesn't yet account for economic fluctuations over time.

These results validate our hypothesis that neural networks can effectively automate and improve credit risk assessment. The low MSE scores indicate high prediction accuracy, while the web interface successfully bridges the gap between technical modeling and practical banking applications. Future work should focus on model calibration with actual transaction data and expansion of predictive features to address the noted limitations.

The successful integration of explainable AI components (SHAP values and natural language reports) addresses the critical need for transparency in financial decision-making, making the system both accurate and interpretable for loan officers. This combination of predictive performance and operational practicality positions INTELLISCORE as a viable solution for modernizing credit assessment in emerging markets.

Chapter 5

Conclusions , Limitations and Future Work

This section will detail the several issues we faced across the development of this project, issues we still have not overcome, and the future work that shall be required to eventually have our product reach a stage in development that makes it a complete and sellable product.

5.1 Limitations and issues faced:

Project genesis and scope:

The idea itself although proposed by Meezan Bank was too vague and could not be understood as a concrete answer for what was required, the base description stated an AI based credit scoring system, no further specifications were mentioned regarding the features, intended users, expected model behavior, or evaluation criteria. However, our team's interest in further pursuing the machine learning field piqued our interest in this project as this would also be a worthy learning experience to understand the functionality of a credible banking system.

After several meetings we came to an understanding that Meezan's requirements were simply a credit scoring system, the rest was up to us. To improve our project scope, we then integrated a dashboard system, a user-friendly UI which could be used by both Meezan employees and regular customers alike. We also sought to integrate a reporting system via a rag-based approach (will be discussed later on).

On the other hand, the project's trajectory was disrupted multiple times due to inconsistencies in stakeholder requirements as in a later meeting with Meezan Bank our scope was narrowed to a credit scoring system for their new bike loans program where we would target the credit scores of those specific applicants. We perceived this to be our final focus however in another meeting down the line we were instead told to dictate our app based on car loans. These abrupt changes created confusion, affected our development schedule, and hindered our ability to build a stable, well-scoped product.

Data (Major issue):

A massive need for any machine learning project is the data, this however ended up becoming our biggest problem in the end.

In our situation, we could have procured an online dataset at any point and trained our model on that, however that would then simply be a generalized credit scoring system. The need for Meezan bank's data specifically was to cater our application to Meezan bank's scoring model.

Our model which would be trained on the features and scores assigned by the bank would have been trained to think and act like a Meezan employee that would normally handle the scoring yet on a level above as it would also learn new underlying patterns across the data that even the employees miss, to generate scores that have an increased depth to their reasoning, what would function as a black-box model would eventually sway from the formula Meezan uses to purely focus on the existing record patterns to assign scores to new individuals.

Unfortunately, perhaps due to a communication or an understanding gap between our team and Meezan bank's team, the industry side refused to cooperate as they did not understand our need for their data. Across several meetings they told us to just generate fake data or to use a dataset online, failing to understand why exactly we need their data. At several points throughout the discourse of this project we asked for an AI/CS expert from their end to bridge the gap and translate our issues to them and theirs to ours, however this was never addressed and we were instead linked up with an individual from the Risk Assessment department who further complicated the situation due to a lack of understanding over AI model logic. Privacy concerns also arose as they worried our handling of the data may violate Shariah Compliance Laws. To address these, we offered them viable solutions, firstly offering to have our entire team sign an NDA to ensure the data wasn't misused, secondly, we asked for anonymized data meaning the records we would possess had no way of being linked back to any single individual as we didn't need the names, CNIC numbers or social security details of any individual. These records would contain data pertaining to statistics only, meaning including columns like income, asset value, residence status etc. With data as such that has no information relating to a certain individual, our data becomes fully anonymized as its now just financial data that could literally be anyone. Despite us addressing these issues, we were rejected any possibilities of the actual data for a while.

To cater for this we then acquired Meezan's bike loan form to get the relevant fields that customers might enter data for to apply for a bike loan, using this we generated logical synthetic data that we scored on our own devised scoring formula, that we then trained a model on, this however was also not accepted by Meezan as they didn't believe we had the expertise or educational background to accurately assign weights to score individuals. Due to the communication gap, they also believed a Blackbox model was an inherent negative which we couldn't convince them of to be false despite several discussions.

We then came up with three new possible solutions for Meezan. We prepared a HIES dataset collected by the Pakistani government containing details of household income statistics for houses and individuals for the years 2018/2019; by catering this to our needs we prepared a legitimate sample dataset that represented actual Pakistani individual's financial standings. This data was highly encrypted and had several data related issues and missing values etc. which had to be dealt with before proposing it as our actual dataset.

The proposed solutions included the following;

- Meezan bank gives us their scoring formula using which we can score our existing records and aim to match actual Meezan scoring logic.
- Meezan bank scores our HIES dataset and we use that to move ahead.
- We develop our own scoring formula through intensive research and credible sources and apply that on the dataset.

Once we have this prepared dataset, we can thus train our model on it accordingly, a possible issue raised here would be that the model would simply be scoring the newer records based on the formula itself, this would hold true to an extent but only at the beginning, as newer records are added to our dataset through applications, the model would eventually converge to a point where its no longer just scoring based off a formula but instead based on hidden correlations between the data points to generate scores. Actual data from the bank would completely mitigate this, however eventually that came to fruition as we finally got an NDA signed an agreement to use Meezan's data which is what we'll move hopefully forward with, this report however is based off the model's working on our synthetic generated data.

As mentioned before, had we been aware of the issues we'd face with financial data sharing, there was a high possibility we'd approach the problem with a completely different mindset and plan, something we will ensure to be well aware of when and if working with any banks in the future.

Model:

We now look towards issues with the model. Due to it being a relatively large amount of testing, we had to utilize free GPU access via Google Colab and Kaggle to further clean, enhance and train our dataset, access to a fulltime GPU could have greatly eased up this burden.

Coming to the actual model, we browsed through several possible ML algorithms i.e. KNN, decision trees, Linear regressors etc. and eventually ended up on Neural Networks which defers from the explainable AI side of things ensuring a Black-box model for scoring. Testing several hyperparameters on this was also relatively time consuming especially since we had to retrain our whole model on the dataset for different models and hyperparameters.

Webapp Backend:

For the Backend we used Django, as it offered a wide range of libraries (authentication modules etc.) and APIs to develop a webapp, getting to know and learn its functionality was a challenge due to our unfamiliarity with the tech stack.

Within Django, a major issue we encountered was connecting the backend logic to the frontend logic for which we struggled with what tech stack to implement, eventually deciding on HTML and Tailwind (a CSS library) for styling.

We also wished to integrate a RAG based model for the report generation however due to it using an open source resource intensive LLM (Qwen 2.5), it had to import to generate the report, our system's computational resources could not handle that workload, so we instead tried several other LLMs of variable sizes , some generated poor reports, others were again too heavy for processing on local systems so we ended up at a lightweight Gemini LLM called through an API key for report generation.

Webapp Frontend:

The frontend was ten times more challenging as opposed to the backend in this situation. For starters several libraries were very limited in terms of the functionalities they offered and what we were looking for; after browsing through multiple options, we chose HTML coupled with a CSS library named Tailwind. We aimed to recreate our proposed layout in the wireframes exactly for our frontend however handling containers etc. was a nuisance.

Our dashboard itself became a major issue as we couldn't figure out how to import charts onto our webapp, as well as integrate our charts to reflect statistics from both our existing data and as the user's inputs, for both of these we put a lot of effort into our views.py file, this was the gateway to connect our backend and frontend seamlessly as it used our backend logic to pass relevant context to our frontend html pages and caused several errors when configuring.

The reports page was also really difficult to integrate as our generated report through the API kept falling out of the container's range on the frontend, secondly, we wished to implement a feature to save and print your reports which also caused problems as the reports kept getting cut off when being saved or printed.

DB integration:

By default, Django uses SQLite3 as a database which also offers a great admin panel which can be used to handle data and records from the admin side, however this was integrated into our main app itself and we wished to separate our DB and our main app.

For this we referred to PostgreSQL, this enabled us to have a separate PGadmin application to instead control and manage our data as well as also allowing us to perform SQL based queries for analysis on the said data, a feature SQLite3 wasn't offering, re integrating our entire data into this new DB caused several errors. We also tried importing our existing input form data from SQLite3 into our Postgres DB but weren't able to due to formatting issues.

5.2 Future Work:

While this project can be a solid product to be used by either Meezan employees or general customers, depending on who Meezan targets it to, there are still several improvements that could be made to the actual product to perfect it.

UI/UX:

For starters, while UI and UX had been cared for to a massive extent in general, consistency across pages, efficient error handling and warnings, a theme resembling Meezan's colors but also being different enough to be eye catchy and easy in terms of visual load. There were still changes we can add to make our UI reach its peak.

Possible additions:

- Multiple languages to cater for users that aren't familiar with English.
- Dark mode based on user preference.

- Option to make text and icons bigger for visually impaired individuals.
- Text to speech and speech to text capabilities for impaired individuals.
- Customizable layout i.e. color and design choices for users to make the app more interactive.

Data:

With the use of actual and increased Meezan Bank's financial data, our model would greatly improve as it could directly then act and think like a Meezan employee when dictating scores for individuals. Having reached an agreement on the data and having signed the NDA, for the case if we do eventually get access to data we'll rain our model on that, otherwise Meezan will give us a green light to continue with our synthetic data.

Training on actual data would also work amazingly as individuals who apply could be ensured that they won't face any bias for their scoring while also being judged as if by a Meezan employee thus getting an idea of their current standing in relation to other previous applicants who also got their scores assessed. They can thus see what they need to improve on to get a better score and what score they exactly need to pass the criteria for a bank/car loan.

By training our model on existing Meezan data, we could also guarantee ourselves a fail-safe for avoiding expertise concerns that the bank initially had, as the scoring would have already been done by their own employees, they wouldn't have to worry about us misassigning weights due to a lack of knowledge in the field.

As of now, we have yet to be supplied with data of around 1000 rows, but once we do get more data i.e. 10k+ rows, it could help our model capture deeper relationships and way more insights, furthermore due to delays with data we couldn't perform the same level of rigorous testing we aimed for. With early access to data the model could be greatly improved.

Report generation:

Our current reliance on the Gemini API is only a short-term solution as we keep needing to use new API keys when our usage limits expire, to counter this our Rag model works perfectly as it uses open source LLMs that can perform the same tasks for an unlimited period of time without complaints.

For this usage we need GPU access which If incorporated by Meezan Bank in the future could remove this liability on a whole ensuring a full centralized system with no need for free trial access keys for their report generation model.

5.3 Conclusion:

To end this report, we will discuss our final thoughts and experience with this project.

What once seemed to be a simple enough task was at times made unachievable due to industry related contractual issues. It was through our supervisor's guidance and our own willingness to learn and achieve something that we came to finalize this year long grueling experience. The project gave us great insights into how the industry functions, what problems you'll likely face when dealing with financial institutions and also how to overcome new learning curves and how to function as a team to achieve a significant goal in the end. It also gave us a great experience boost with designing fully functional web applications and an ai model that meets industry standards.

With this we conclude our report, thankyou for your time.

Chapter 6

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