SMART SERVICE PROJECT VOLTA LIMBURG

TEAM 10

[redacted]
Leon Reiß - i6337206
[redacted]

Supervisors:

Prof. Dr. Rudolf Müller

Chandra Tamang

Inhalt

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Executive Summary

This project aims to enhance the operational efficiency of Volta Limburg, a Dutch company specializing in residential heating devices and air conditioning systems. Our analysis revealed that 44% of single-visit repair cases did not require spare parts, suggesting opportunities for customers to resolve some issues themselves with proper guidance.

To address this, we developed a machine learning solution using a random forest model to accurately classify heating system issues as customer-solvable or requiring a technician visit. Key steps included:

- **Data preparation by merging multiple datasets and feature engineering.**
- **Evaluating statistical and machine learning models.**
- **Implementing the optimized random forest model**

The model achieves 71.34% accuracy and 91.14% sensitivity in identifying non-customer-solvable issues while capturing 16.31% of customer-solvable cases. This marks a significant improvement over the current scenario of dispatching technicians for all cases.

Implementing this solution is estimated to save Volta Limburg €109,620 annually by reducing technician hours while promoting environmental sustainability through reduced emissions from travel. The model's scalability allows seamless integration of new data sources like Sqippa sensors, enhancing accuracy.

We recommend proceeding with implementation to position Volta Limburg as an innovative leader in customer-centric service solutions. Ethical considerations like data privacy and environmental impact have been evaluated. The project provided valuable team learning in collaboration, problem-solving, and project management.

1. Introduction

Volta Limburg is a Dutch company specializing in residential heating devices, air conditioning systems, and similar appliances. Their primary business model revolves around all-inclusive rental contracts, where customers pay a monthly subscription fee, and Volta Limburg manages the maintenance and repair of these devices. However, the company is currently experiencing challenges in deploying sufficient technicians to handle all repair and maintenance requests. The overarching aim is, therefore, to enhance the efficiency of technicians and their tasks.

Volta Limburg has already been collecting data on repair and maintenance tasks and has recently begun gathering sensor data from 18 devices using Sqippa technology. This data, while not yet fully utilized or analyzed, holds significant potential for increasing operational efficiency.

In this Report, we explain our approach through all stages of the smart service development, ranging from the general understanding of the business and its challenges, identifying potentials of improvement, conducting best practices from similar business cases, feature engineering for model development, validation of our model developed and further ethical, societal, and managerial implications resulting from our analysis.

The report concludes with a reflection on the team's learning experience and collaboration throughout the project, as well as a summary of the key findings and recommendations for Volta Limburg to implement the proposed smart service solution.

2. Service Design

2.1 Discover Phase: Understanding the Business and the Problem of the Customer

In the first phase of the double diamond, we pursued the goal of identifying patterns and inefficiencies that could be used as a basis for strategies to reduce technician hours. As a first step, we conducted a root-cause analysis to see the cause of technician hours. We differentiated between repair and maintenance activities. For repair tasks, a distinction was made between problems that require multiple visits, problems that can be solved in a single visit, and problems that can potentially be solved by the customer with the help of the call center. Using the data sets made available to us by Volta Limburg we saw that repairs account for most technician visits, namely 59% of the workload. Remarkably, 92% of these repairs are resolved within a single visit and in 44% of these cases no spare parts were used. This suggests that there are opportunities to optimize operational efficiency for repair visits and potentially enable customers to resolve some issues with the right distance guidance. However, also the number of cases where spare parts were used is substantial if we consider that our data set contains 400,000 of them. This is why we also considered the possibility of spare parts availability being an issue when it comes to resolving problems and saving technician hours.

Having those two main problems in mind, we conducted interviews with two Volta employees who are highly experienced in their roles and familiar with the university project and the data provided by Volta and Sqippa.

Colin Glezer, Customer service manager, emphasized that video telephony can help resolve issues remotely, especially when customers have limited technical understanding. He also noted that the wide variety of brands makes it difficult to recognize problems. In addition, many problems could be solved by resetting heaters remotely. He estimated that around 15-20% of problems could be solved by customers themselves with the right guidance.

Pascal Damoiseaux, an experienced service mechanic, noted that out-of-stock maintenance items are rare, usually only affecting older or newly introduced heating devices that require specific parts. This is mostly because of older or new heating devices which need items. Pascal also noted that the seasonality of maintenance has decreased due to mixed heating devices. Furthermore, he pointed out that customers sometimes cause problems by changing the heater settings and he estimates that about 15-20% of the problems can be solved by the customers which is in line with Colin's statement.

Based on the interviews, we again realized that technicians' working time could be reduced if customers could solve 1 out of 5 problems themselves. Despite the high number of cases involving spare parts, a shortage was not confirmed. Therefore, we next explored best practices where companies optimize their problem-identification process, which will serve as valuable input for our task of identifying customer-solvable problems.

2.2 Define Phase: Leveraging AI for Optimizing Field Service Management

AI and data-driven strategies are key to increasing efficiency in field service management. This includes optimizing customer care operations, routes, and work order prioritization. A report by Zuper and Blumberg Advisory Group (Zuper & Blumberg Advisory Group, 2023) highlights the potential of AI to transform field service by personalizing customer interactions and increasing efficiency through automation. We now present two case studies that show how similar challenges in field service management have been overcome using AI.

Case Study 1: Efficient Elevator Repairs Using Machine Learning (Krumholz, 2022)

The first case study highlights an innovative approach to increase service efficiency in an elevator company. The challenge was that technicians were arriving without accurate diagnostics, leading to high costs and inefficiencies. The company introduced a cloud-based fault reporting system, which initially generated many unnecessary fault codes. By combining these codes with the technicians' reports, patterns were recognized, and a predictive model was trained on 200 error sequences. This model predicted the ten most likely faults so that the technicians would know which errors are likely to occur and prepare for them. Additionally, it would even recommend the correct spare parts to bring to the site. The implementation lowered maintenance costs and improved elevator uptime.

Case Study 2: Machine Learning Assisted Troubleshooting Flows (Tan & Pham, 2021)

The second case study is about improving customer satisfaction by using machine learning (ML) to diagnose service problems more efficiently. The aim was to reduce problem resolution time by predicting at an early stage whether a technician would be needed. ML algorithms such as Logistic Regression with Stochastic Gradient Descent (LRSGD), Random Forest (RF), and Xtreme Gradient Boosting (XGB) were used, with XGB performing the best. By using customer data and telemetry data, the model was able to accurately determine when on-site intervention was required. This minimized unnecessary steps, shortened call duration, reduced repeat visits, and improved service times and customer satisfaction.

These case studies demonstrate how AI in field service management can significantly enhance service efficiency and customer satisfaction by providing accurate diagnostics. Implementing these solutions reduced costs, improved problem resolution times, and minimized unnecessary technician visits.

2.3 Value Proposition for Smart Service Solution

Based on interviews, initial data analysis, and insights from case studies, our approach involves implementing a classification system to identify issues that can be solved by the customer and those that cannot. This machine-learning diagnostic tool could streamline the process, reduce technician time, and improve operational efficiency. For Customer Success Managers, this tool will improve the diagnosis process. It can improve customer satisfaction by empowering customers to resolve minor issues themselves, resulting in faster resolution times. For Operations Managers and technicians, it will optimize resource allocation and reduce operating costs by ensuring that technicians are sent to places where they are really needed. The most important performance target for the analysis solution is a general minimization of technician repair ideally up to 25%. The diagnostic tool would be linked to the customer service or resource allocation software and provide an initial forecast of customer solvability based on the available data when the call is made.

3. Selection and preparation of data, and selection of methods

3.1 Data preparation and merging

To set up the foundation for our classification model the selection and preparation of data were crucial. Our process started with the strategic selection of four key tables from the ones provided by Volta: “Data Volta foutcode”, “Data Volta gebruikte materialen”, “Data Volta Monteursbezoeken”, and “Data Volta Foutcode omschrijving”. Choosing these tables was necessary to get a complete view of each incident. By combining the information, we could see when each incident happened, which device was involved, what error occurred, what materials were used, and if the error could have been fixed by the customer.

We started data handling by importing these datasets into R Studio for analysis. We then cleaned and standardized the data, which involved renaming columns for consistency, standardizing date formats, and in the case of “Data Volta Foutcode omschrijving” we added a column that indicates if in general, an error code is customer solvable or not.

Following this, we merged these datasets into a master table called "Monteursbezoeken_TTL" using unique identifiers created from CALL_PREFIX and CALL_SUFFIX. This identifier allowed us to track each incident and determine the visit count for that incident. For example, "123546 1" indicates the first visit for incident 123546, while "123546 5" indicates the fifth visit for the same incident. Being able to identify each incident and its multiple associated visits was crucial for effectively combining the different tables. This table serves as a central repository, linking error codes with corresponding technician visits and materials used, and capturing every aspect of service incidents.

After creating "Monteursbezoeken_TTL", we evaluated which information could be used and which needed to be computed (feature engineered) to predict customer solvability of new incidents. To achieve this, we conducted a descriptive analysis of the complete data set, basing our assumptions on the expertise we gained over the past few weeks and the previously presented insights from interviews with Volta Limburg employees. To ensure that the prediction variables both given and computed will work properly we also used the descriptives to look for irregularities and errors in the data.

3.2 Descriptive analysis

The first issue we encountered was that some devices lacked a "year of construction" value, making them difficult to use. Therefore, we excluded these devices from our analysis. Additionally, we observed that some incidents were recorded before the construction year of the device, meaning the incident date was earlier than the device's construction date. These records were also excluded.

After addressing these issues, we found a major anomaly in the distribution of incident occurrences over time. Eleven specific days between 2017 and 2023 accounted for 40% of all cases, mainly in January and February each year. This unusual clustering could skew our analysis and affect the reliability of our predictions. To handle this, we created two data sets: one with the anomalous data and one without. We used both for further analysis. We also plan to discuss these anomalies with Volta Limburg to understand potential operational or data entry errors that might explain these irregularities.

Figure 1 shows the anomalies detected for the year 2019.

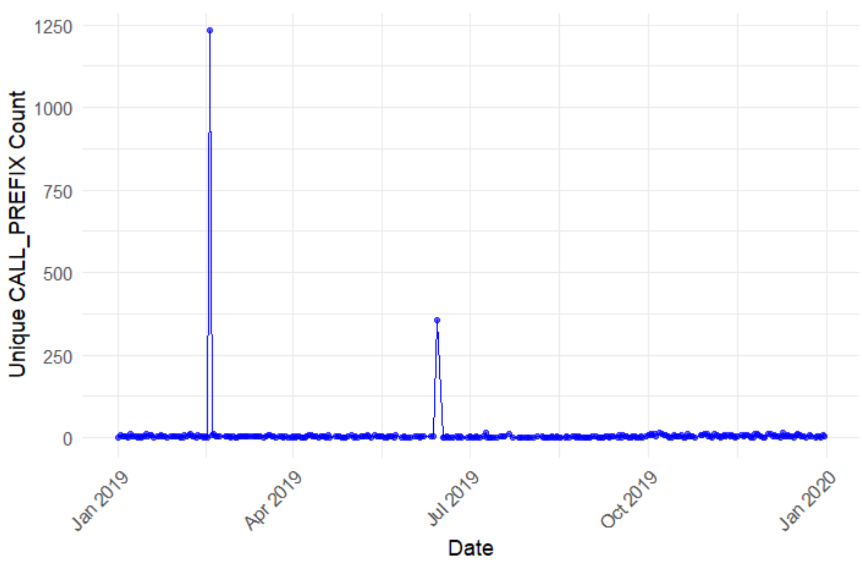

Figure 1 Anomaly analysis for errors per date.

Another finding was our initial assumption that customer solvability might vary based on the product description, meaning some models might have more or fewer customer-solvable errors. However, our analysis showed this was not the case, so we excluded product description as a predictor. Figure 2 illustrates that for only a few descriptions, totaling 53 out of the 32,000 observations, the rate of customer-solvable errors deviates from the average of around 25%.

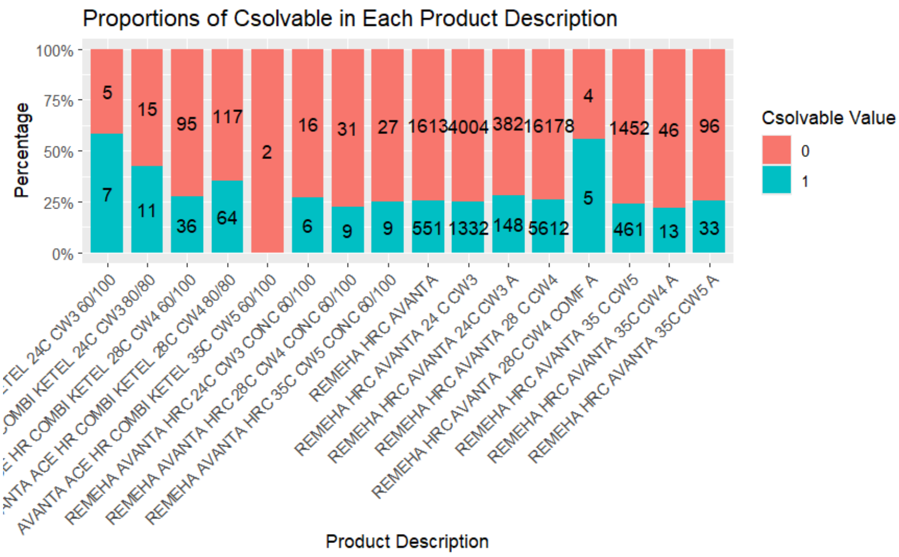

Figure 2 Analysis of customer solvable issues based on product description.

We examined the trend of customer solvability over time, see Figure 3, and observed a slight decrease in solvability as devices aged, followed by a minor increase in older devices, a pattern that provided minimal actionable insight.

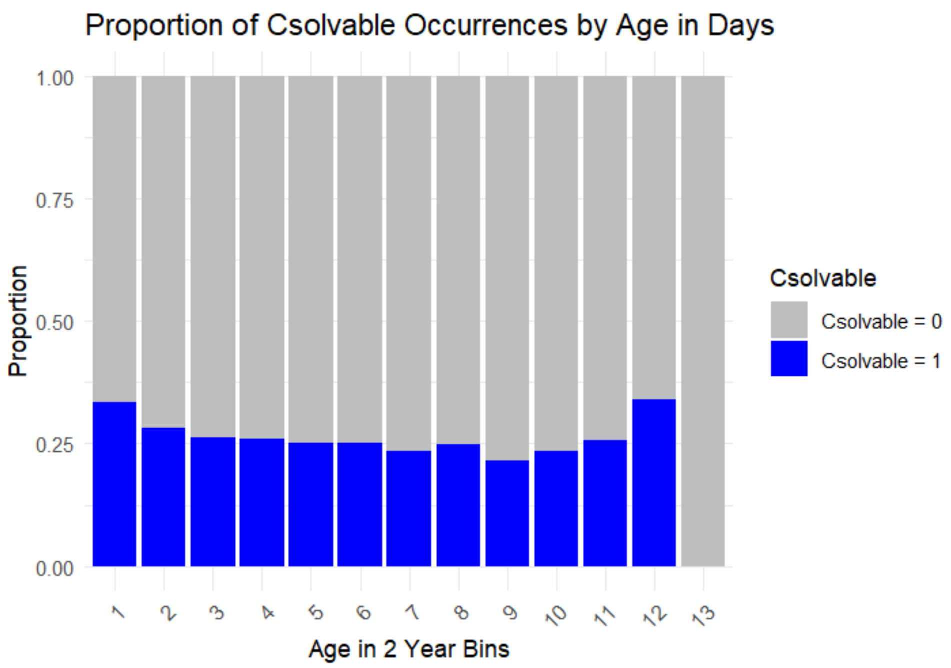

Figure 3 Analysis of customer solvable issues based on device age.

Based on this, we decided to build our prediction model using our and Volta's understanding of predicting customer solvability for new issues. We assume that by examining the history, frequency, and customer solvability of past error codes, along with the number of materials used for each error, we can determine if a new error code will be solvable by the customer.

For example, if a device frequently only requires a water refill, it is likely to need a water refill again because the owner might not realize this and thus call for help. On the other hand, if many materials were needed to fix past errors, it likely means that upcoming errors might also require a technician.

3.3 Feature engineering

To achieve this, we used the error codes, the quantity of materials used, their dates, and whether the error code is customer-solvable to compute variables such as the date of the last error code in days, days since the last error code, and the quantity of materials used in the last error. We used dates in days because numeric values are easier to calculate than using actual dates. This was done by setting the first of January of the earliest year in the dataset as day one and calculating from there.

Table 1 provides an overview of the variables used for the model, indicating whether they were provided by Volta, computed, or externally acquired.

Table 1 Variables used for model building.

Variable Name	Description	Type	Source
FAULT_CODE	Specific problem identifier for each incident.	Character	Given
CALL_PREFIX	Incident number, serving as the primary identifier for service calls.	Numeric	Given
CALL_SUFFIX	Indicates the visit order for a given incident number.	Numeric	Given
CREATE_DATE	Date when each incident was recorded.	Date	Given
UnitNo	Identifier for the specific unit or device serviced.	Character	Given
Csolvable	Indicates if an issue could be solved by the customer.	Numeric	Given
Identifier	Concatenation of CALL_PREFIX and CALL_SUFFIX to uniquely identify each visit.	Character	Computed
Age_in_days	Days from the device's installation to	Numeric	Computed

	the incident date.		
current_date_in_days	Days from a reference point to the incident date.	Numeric	Computed
Last_Error_Code_Before	Error code of the last incident before the current one.	Character	Computed
Date_Last_Error_Code_Before	Date of the last error code before the current incident.	Numeric	Computed
Days_since_last_error_code	Days between the current incident and the last error.	Numeric	Computed
Csolvable_Last_Error_Code_Before	If the last error before was solvable by the customer.	Character	Computed
Qty_Materials_used_Last_Error_Code_Before	Materials used during the last incident with the same error.	Numeric	Computed
CS_Error_Code_Count_Before	Count of customer-solvable errors before the current one.	Numeric	Computed
T	Temperature on the day of the incident.	Integer	External

P	Atmospheric pressure on the day of the incident.	Integer	External
R	Rainfall amount on the day of the incident.	Integer	External
Max_Delta_T	Max temperature change five days preceding the incident.	Numeric	External/Computed

After computing the variables, we performed another data-cleaning task, replacing NA values with meaningful alternatives. Table 2 provides an overview of the replacements made:

Table 2 NA replacements

Variable Action	Explanation
Last_Error_Code_Before -> "none"	No error code occurred before, so "none" to highlight that there is no previous error.
Identifier_Last_Error_Code_Before -> "none"	No error code occurred before, so "none" to highlight that there is no previous error.
Date_Last_Error_Code_Before -> -99	No error code occurred before, so "-99" to have a replacement value for no date.
Days_since_last_error_code -> -99	No error code occurred before, so "-99" to have a replacement value for no date.
Csolvable_Last_Error_Code_Before -> "none"	No error code occurred before, so "none" to highlight that there is no previous error.
Qty_Materials_used_Last_Error_Code_Before -> 0	No error code occurred before, so "0" to highlight that 0 materials were used.
Error_Code_Count_Before -> 0	No error codes ever occurred before, so "0" to highlight that there were 0 error codes before.
CS_Error_Code_Count_Before -> 0	No error codes ever occurred before, so "0" to highlight that there were 0 error codes before.

After creating the variables, we observed that they did not significantly impact customer solvability. For instance, the days since the last error code did not show a clear trend over time, as shown in Figure 4, and other variables exhibited similar patterns.

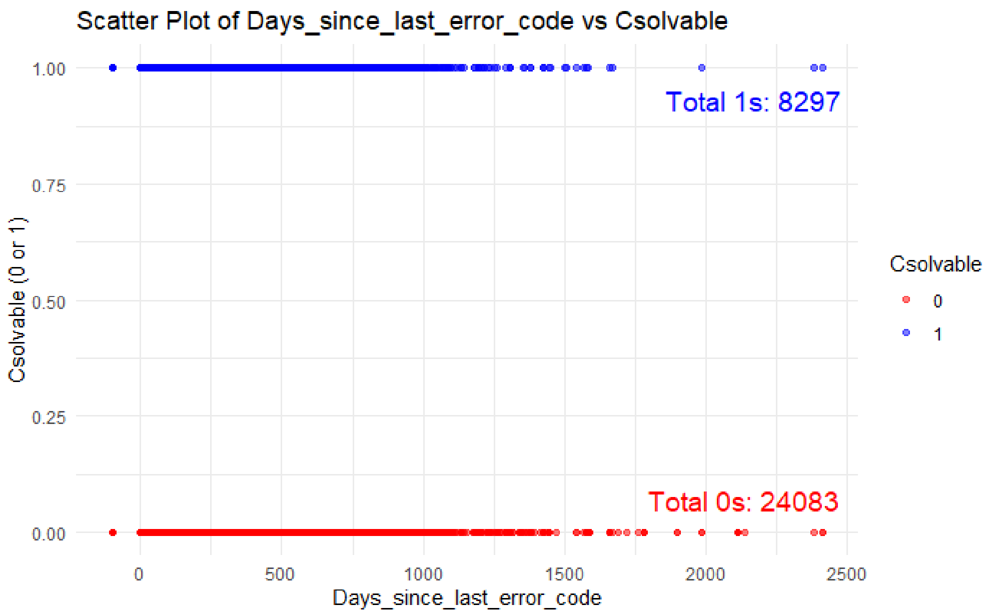

Figure 4 Plotting variables against customer solvable issues.

With this in mind, we focused on capturing as much predictability within the data as possible by selecting appropriate models and tuning them to predict customer solvability for new incidents effectively.

3.4 Model selection

We selected and evaluated various statistical methods and machine learning models based on our extensive data preparation and preliminary insights. Our goal was to identify a model capable of accurately predicting customer solvability for new incidents.

We began with logistic regression to establish a baseline, but its AUC of 0.536 indicated the need for more advanced models. Decision trees were considered next for their ability to capture non-linear relationships, but their tendency to overfit required us to look further. We then employed the Random Forest algorithm, which combines multiple decision trees to improve accuracy and stability. This model balanced specificity and sensitivity well, achieving an accuracy of approximately 73% and effectively handling our dataset's complexity. Finally, we explored Gradient Boosting Machines (GBM) for their accuracy and robustness against overfitting. Despite this, Random Forest remained the preferred model due to its superior performance metrics.

The Random Forest model was particularly effective in identifying customer-solvable incidents, achieving a detection rate of around 10% and maintaining a very low false positive rate (0.1%). This ensured reliable predictions and minimized the risk of incorrectly assuming customers could solve issues that required a technician. By implementing the Random Forest model with rigorous evaluation and tuning, we have enhanced Volta Limburg's operational efficiency, optimizing technician dispatch and improving customer service.

4. Service Validation

This chapter outlines our approach for model implementation and training, presenting the analytical results in terms of the performance targets set in the service design section and common measures in academic literature. Among the models tested, the random forest model performed best. Here, we will detail the training process, model evaluation metrics, and the significance of feature importance in the model.

4.1 Model Implementation and Training

The random forest model was chosen due to its robustness and effectiveness in handling a large number of predictor variables and complex interactions. The dataset used was cleaned to exclude the anomaly dates detected in previous analysis and comprised 14,746 samples with 13 predictors and 2 classes, namely customer solvable: 'No' and 'Yes'.

The model was implemented without preprocessing as standardization or normalization did not lead to better performance. The application of these preprocessing techniques was therefore considered unnecessary and could negatively affect our results (Raju et al., 2020). The model was trained using a 5-fold cross-validation approach to ensure a reliable estimation of model performance. To ensure the validity of our performance metrics even on unseen data, we used an additional holdout set of 20% to evaluate the model's performance.

The performance of the random forest model was assessed using several metrics, which are standard in academic literature, including accuracy, sensitivity (recall), specificity, and the Receiver Operating Characteristic (ROC) curve along with the Area Under the Curve (AUC) (Fawcett & Provost, 2013).

4.2 Evaluation Metrics and Results

Accuracy represents the proportion of true results (both true positives and true negatives) among the total number of cases examined. The accuracy of the model was 71.34%, with a 95% confidence interval of 69.85% to 72.80%. Sensitivity, also known as recall, measures the proportion of actual positives (in our case “No”) correctly identified by the model. The model achieved a sensitivity of 91.14%, indicating it misclassifies less than 10% of the cases as customer-solvable even if it is not customer-solvable. This results in a rather low portion of potentially dissatisfied customers.

Specificity measures the proportion of actual negatives (in our case “Yes”) correctly identified. The model's specificity was 16.31%, which, although low, represents a significant improvement from the initial state where every case was classified as 'No'. Speaking differently, instead of sending a technician to every malfunction, we can identify 16.31% of cases in which sending a technician is not necessary and phone guidance could be sufficient to solve the issue.

The ROC curve (Figure 5) is a graphical representation showing the trade-off between sensitivity and specificity. The AUC value indicates the degree of separability achieved by the model, with higher values representing better performance. The model achieved a ROC value of 0.567 with mtry = 4, indicating a moderate ability to distinguish between the classes.

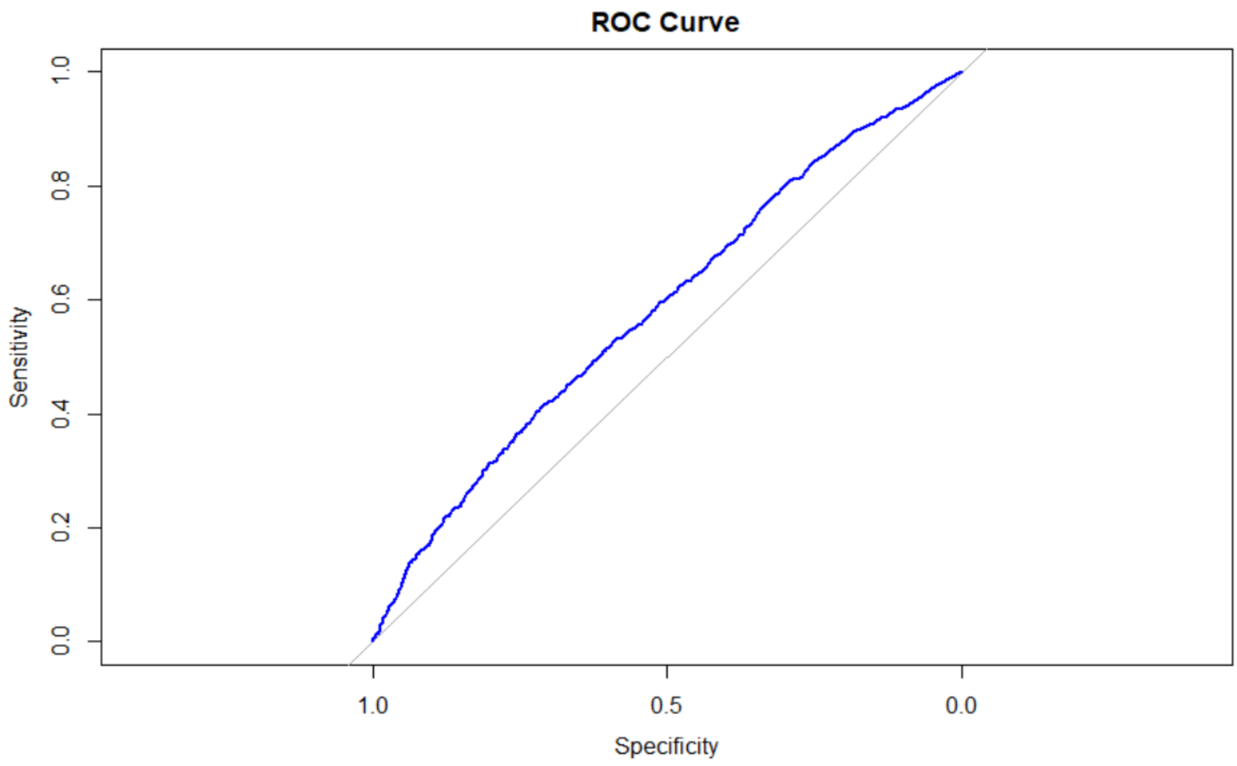

Figure 5 ROC curve of the random forest model.

4.2.1 Confusion Matrix and Statistical Summary

The confusion matrix on the holdout dataset provides a detailed breakdown of the model's performance:

Actual **Prediction**	No	Yes
No	2470	816
Yes	240	159

Table 3 Statistical summary on holdout-dataset

Statistical Summary	
Accuracy:	0.7134
95% CI:	(0.6985, 0.728)
No Information Rate:	0.7354
P-Value [Acc > NIR]:	0.9987
Kappa:	0.0919

Sensitivity:	0.9114
Specificity:	0.1631
Pos Pred Value:	0.7517
Neg Pred Value:	0.3985
Prevalence:	0.7354
Detection Rate:	0.6703
Detection Prevalence:	0.8917
Balanced Accuracy:	0.5373
'Positive' Class:	No

Table 3 provides the statistical summary of the Random Forest model on our holdout dataset. Besides the previously mentioned values, The No Information Rate (NIR), which represents the accuracy that would be achieved by always predicting the most frequent class, is 73.54%. The p-value for accuracy is greater than the NIR is 0.9987, signifying that the model's accuracy is not significantly better than random guessing. However, The Kappa statistic of 0.0919 indicates slight agreement beyond chance between the model's predictions and the actual classifications.

4.3 Testing Stability

To test the stability of the random forest model, we printed the confusion matrices per fold in the cross-fold training process.

Fold 1:

Actual **Prediction**	No	Yes
No	9247	3067
Yes	1598	833

Fold 2:

Actual Prediction	No	Yes
No	9897	3357
Yes	948	548

Fold 3:

Actual Prediction	No	Yes
No	9281	3104
Yes	1564	796

Fold 4:

Actual Prediction	No	Yes
No	9750	3296
Yes	1090	609

Fold 5:

Actual Prediction	No	Yes
No	9220	3113
Yes	1625	787

By looking at these confusion matrices, we conclude that the results do not differ significantly in each fold, proving a rather stable behavior of our model. The model therefore is not overly sensitive to specific samples included in each training and validation set and over and underfitting does not seem to be an issue.

4.4 Feature Importance

Finally, we analyzed the importance of each feature we engineered as our predicting variables. The importance of each feature was assessed using the Mean Decrease in the Gini index. This metric indicates how much a given feature contributes to reducing uncertainty or impurity in the model's decisions. Figure 6 graphically illustrates this.

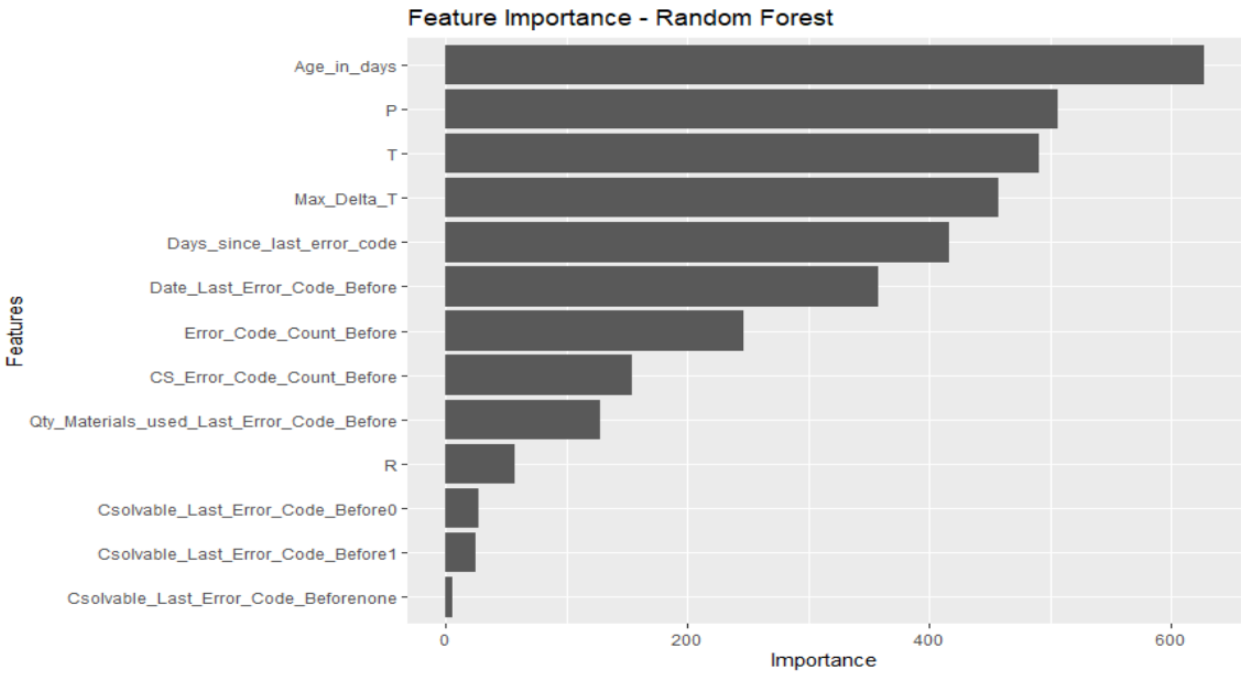

Figure 6 Feature importance for the random forest model.

The most important features, ranked by their Mean Decrease in Gini index, are as follows: 'Age in days of the heating system' is the most significant feature with a Gini index of 627.34, followed by 'Air pressure' with a Gini index of 506.17. 'Temperature' and 'the maximum temperature delta within the last 5 days' are also highly influential with Gini indices of 490.58 and 456.80, respectively. 'The days since the last error code occurred' has a Gini index of 416.48, and 'the date of last error code before the current' follows with a Gini index of 357.42. Other important features include 'the number of Error codes before' (246.02), 'number of customer solvable error codes before the current' (154.79), and 'Quantity of materials used before the last error code' (127.33).

Other features such as ‘indication of Rain’ (57.60), and if the last error code that occurred was ‘customer solvable’ (24.99), ‘not customer solvable’ (26.88), or ‘no error code occurred’ (5.27) seem to have less predictive power.

4.5 Conclusion on Service Validation

The random forest model demonstrated strong performance, particularly in sensitivity, making it a reliable choice for our service through a low rate of misclassifying customers' issues as customer-solvable. While the specificity is currently lower than desired, the model's ability to start recognizing 'customer solvable' cases marks a significant improvement from the current state where for all cases technicians are sent to the customer. The feature importance analysis highlights the key predictors influencing the model's decisions, providing actionable insights for further improvement, and understanding of the underlying data patterns. With our current pipeline, we provide Volta Limburg a solid foundation to extract some predicting variables from their current data collection. Even if our model performance does not entirely fulfill our business performance targets of a 25% reduction in technician visits, we developed a foundation to further work on and we expect further improvements through the incorporation of all heating device types as well as the incorporation of Sqippa sensor data into this feature pipeline.

5. Ethical, Societal, and Managerial Implications of our Smart Service Solution

5.1 Ethical and Societal Considerations

The implementation of a random forest model by Volta Limburg to determine whether heating device issues are customer-solvable introduces several ethical and societal considerations. One significant concern is data privacy and security. The model must handle customer data responsibly, ensuring anonymity and securing data against breaches, in compliance with regulations such as GDPR. However, the data processed by our model can be considered less sensitive, and the model operates within internal IT infrastructure, which mitigates general security concerns.

Another aspect affected by our smart service solution is the environmental impact. Reducing unnecessary technician visits and replacing them with guided phone calls results in overall emission reduction. With climate change being one of the major challenges of today's society, every company should strive to reduce its environmental impact. Our solution can be seen as another step for Volta Limburg towards becoming a greener company.

5.2 Business Value Judgment

Based on our discussions with Volta Limburg, we have assessed the business value by estimating a €50 hourly wage, as advised by Collin Glezer, the manager of Customer Service. We have determined that, on average, 1.5 hours are spent on each case that could have been resolved by the customer but wasn't. Therefore, our model, when successfully identifying customer-solvable cases, leads to savings of €75 per case by avoiding unnecessary service involvement. Additionally, we assume a cost of €10 for misclassified non-customer-solvable issues due to the time spent attempting to fix those issues. Besides this monetary loss, the inconvenience to customers caused by misclassification remains subject to further managerial consideration.

To assess the monetary value of our solution, we conducted the following calculation. On average, Volta Limburg handles 87,000 service issues per year, of which 60% are repair cases, resulting in 52,200 repair cases per year. Twenty-five percent of these cases are classified as customer-solvable issues, resulting in 13,050 customer-solvable cases per year. Our model is currently able to identify 16% of these customer-solvable cases, resulting in 2,088 customer-solvable cases identified. Furthermore, we misclassify 9% of the repair cases as customer-solvable even if they are not, resulting in 4,698 misclassified cases. These calculations result in the following business value:

- Total savings from correctly identified cases: 2.088×€75 = €156.600 per year
- Total costs from misclassified cases: 4.698×€10 = €46.980 per year

Thus, the net savings from implementing the model are calculated as:

- Net Savings = €156.600 − €46.980 = €109.620 per year

These cost savings could be further increased through additional model improvements, as explained in previous sections. However, customer dissatisfaction due to misclassification could negatively affect our calculations. Assessing the full monetary impact of these cases is challenging and should be discussed by the management.

5.3 Managerial Recommendations

Looking forward, the scalability and adaptability of our model present significant opportunities. The plug-and-play capability of the system allows for the seamless integration of new devices and the inclusion of more sophisticated predictors, such as those from the Sqippa device. This adaptability not only enhances the model's accuracy and efficiency but also extends its applicability to a broader range of equipment and scenarios. Through an expansion of the used dataset and refinement of the algorithm, we anticipate these improvements will lead to greater cost efficiencies and increased customer satisfaction.

Moreover, the ease of integrating new technology into our model means that initial investment and implementation efforts can be leveraged over time, yielding higher returns as the system grows. This forward-thinking approach aligns with our strategic goals of enhancing service quality and operational efficiency through technology.

Given these considerations, we advise proceeding with the implementation of the model. Doing so not only prepares Volta Limburg’s infrastructure for future advancements but also positions Volta Limburg as a leader in innovative, customer-centric service solutions. This proactive step ensures they remain competitive and responsive to evolving market demands and technological capabilities.

6. Team reflection

Over the past four months, our team embarked on a project that provided substantial learning and development. Here, we outline our initial assumptions and expectations and retrospectively analyze them to increase our understanding of our strategies' effectiveness.

From the outset, we were unified in our goal to ensure the project's success. To facilitate collaboration, we agreed to meet every Wednesday from 10:00 AM to 6:00 PM. This regular schedule minimized the need for weekly planning and set clear expectations for everyone. Initially, we faced challenges due to insufficient information from our client, Volta, leading to unnecessary rework. However, as we progressed, the benefits of our approach became evident, particularly in the latter stages of the project.

During the discovery phase, we collectively worked to understand Volta's needs thoroughly. We formulated and regularly revisited the problem statement at each meeting to maintain alignment. Although having a designated "lead consultant" might have expedited this process, we found value and enjoyment in this inclusive and collaborative approach.

As the project advanced, time constraints grew more pressing, prompting us to enhance our efficiency by dividing into pairs or working individually on specific tasks. We strategically assigned tasks based on clarity and complexity to maintain a comprehensive perspective and leveraged individual strengths—ranging from programming and data transformation to language skills and storytelling. This method significantly boosted our efficiency, although it introduced some coordination challenges.

In conclusion, while there were opportunities for greater time efficiency, our collective satisfaction with the teamwork and lessons learned remains high. Reflecting on our experiences, we recognize both the strengths of our collaborative efforts and the areas where we can streamline processes for future projects.

7. Conclusion

In conclusion, this project developed a machine learning solution to help Volta Limburg optimize its field service operations by identifying heating system issues that could potentially be resolved by customers themselves with remote guidance, avoiding unnecessary technician visits. Through data analysis, interviews, and case studies, the team designed a value proposition involving a classification system using a random forest model to predict customer-solvable issues.

The model achieved an accuracy of 71.34% and balanced sensitivity (91.14%) with lower specificity (16.31%), allowing it to reliably identify non-customer-solvable issues while still capturing a reasonable portion of customer-solvable cases. Key predictive features included system age, weather conditions like temperature and pressure, and details about prior error codes and materials used.

Implementing this solution is estimated to save Volta Limburg around €109,620 per year by reducing technician hours while contributing to environmental sustainability. The model's adaptability, ability to integrate new data sources like Sqippa sensors, and alignment with Volta's innovation goals were highlighted. Ethical considerations like data privacy and environmental impact were also discussed.

Overall, the team recommends proceeding with implementation, positioning Volta as a leader in innovative, customer-centric service solutions. The project provided valuable learning experiences in collaboration, problem-solving, and project management for the team.

8. Literature

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