MACHINE LEARNING APPROACH FOR THE PREDICTION OF THE STATUS OF TANZANIAN WELLS [COMP4030 CW2 - Data Science and Machine Learning]

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***Abstract*—This paper details our approaches and results for the COMP4030 CW2. The goal was to predict the status ('Functional', 'Functional - Needs Repair' & 'Non-Functional') of water wells in Tanzania. This is important as not only does knowing the status of the well help keep the total percentage of functioning wells higher, but it also allows for more effective spending on repairs. The most important features included 'age', 'season_when_recorded', 'height_above_sealevel' & 'extraction_type'. The best performing models were XGBoost and BaggingClassifier.**

***Index Terms*—Machine Learning, Data Science, Classification, Water Pumps**

I. Introduction

A. Research Questions

What factors are most important for determining the status of a well, and how accurately can we classify wells based on these features?.

We choose this question because we are interested in the factors that determine the status of a well, and using ML to try to classify these wells. Follow-up questions to this question could include:

- How does the accuracy of the classification model vary with different feature sets and classification algorithms?
- Could we use our results to ensure that wells are built and repaired so that fewer wells are non-functional?

B. Dataset

The chosen dataset is from the Tanzanian Ministry of Water and contains information on the status of wells in Tanzania. This dataset has 59400 rows, with 40 different features. These 40 features could be broken down into three subgroups: a) Geographic Location of the Wells. b) Management of the wells. and c) Water Condition of the wells. The dataset is originally split into 2 different files, one for labels and one for the actual data. These can be merged easily with pandas through left join on the "ID" column.

Fig. 1 shows the distribution of the target variable, which is the status of the well. We can see from this that we might need to oversample the 'functional needs repair' class, due to class imbalance.

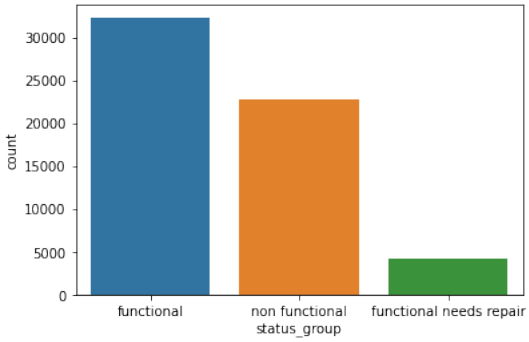


Fig. 1: Distribution of the target variable

C. Management Structure

A requirement of this project was to work separately within our pairs and try different techniques to solve the problem. To not lose important insights, we communicated our results throughout the project. We followed a 'Christmas Tree'-like approach for each stage: 'Data Analysis', 'Data Pre-processing' & 'Data Classification'. Each section was performed individually, before combining our results and moving out the next section. This process wasa performed cyclically, such as re-visting the Preprocessing step after the first Classificiation step. See Fig. 2

This results in two main benefits. Firstly, it allows us to research a large number of approaches, which provides a higher chance of finding a powerful approach. Secondly, the combination of approaches that resulted might have never happened when working individually, which may provide more optimal results.

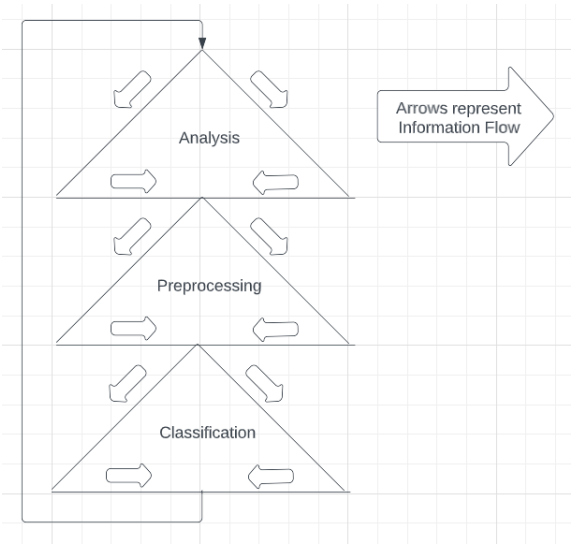


Fig. 2: Management Structure

II. Literature Review

One study by Pathak et al. (2023) [1] compared the performance of TabNet, a sequential attentive classification architecutre designed for tabular data, and tree-based approaches such as XBBoost. They found that TabNet outpeformed XGBoost, boasting an 83% accuracy compared to XGBoosts 78%. TabNet makes use of Transformers, a machine learning algorithm which uses self-attention to differentially weight the significance of each part of the input. A point of note is that TabNet does not require feature engineering to perform at these standards. We have not used TabNet in our report, as our primary goal was to showcase an end-to-end machine learning solution, and this includes feature enginering. However, it provides an interesting comparision.

Pham et al studied fully connected neural networks on the Pump it Up dataset [2], settling on a model with 7 hidden layers and cross-entropy loss as the loss function. Their trained model achieved a 78.6% accuracy rate on the test dataset. Although our project has prioritized tree-based methods for their speed, it would be interesting to compare our results with those of a neural network.

Jithin Paul also undertook a study on the Pump it Up dataset, experimenting with different models to test for the best results [3]. He proposed four methods, RandomForest, DeepLearning, LogisticRegression & AdaBoost. The results showed that RandomForest, was the most accurate model, achieving a mean accuracy of 81.18% on the test dataset. This finding demonstrates that tree-based models perform exceptionally well on this dataset, which motivated us to use more sophisticated tree-based methods in our own work.

III. Methodology

A. Data Analysis

When conducting data analysis, the python library Seaborn [4] was our primary data visualization tool. Seaborn offers more visually appealing graphs than MatPlotLib.

1) Thomas: Thomas visualized the correlation between 'construction_year'and other features in the dataset. 'construction_year' had a number of missing values, therefore these graphs could determine the possibility of using other features to impute the missing values.

2) Jason: Jason checked the number of missing and unique values across 38 features provided.He wanted to identify features that would require imputations due to missing or invalid values. In addition, this step allowed him to distinguish features which would have to be recategorised due to the large number of unique values present. He also generated Count Plots for each of the previously mentioned features based on water wells' status. These plots allowed him to visualise the distribution of the wells' status based on features. Thus, making it easier to identify features that could possibly influence the status of a water well.

B. Data Preprocessing

1) Thomas: Thomas performed imputation of the lat & lon missing values by applying grouped mean imputation. The data was grouped by 'ward', 'lga' and then 'region'. This ensured that any missing values in either 'ward' or 'lga' did not result in missing lat / lon values. This also provides more accurate results than just 'regular' mean imputation, as the imputed values are localised. The Funder & Installer columns contained 1000s of unique values. In Thomas' approach, he decided to group the column into categories: 'Charity', 'Government', 'Local Government', 'Private', 'Religious', 'Foreign', 'School' & 'Unknown'. This was done to simplify the dataset, making it easier for the model to learn the distribution. Since, the columns had crossover between the values, this can be done in 1 step. Thomas also used the SMOTE-ENN algorithm from imblearn [5], to balanced the dataset, specificall the 'Functional - Needs Repair' class. Imbalanced datasets could potentially affect model performance, especially in tree-based models. Finally, 'gps-height' was normalised using a custom MinMaxScaler and a custom Z-Score Scaler. This was due to the prevelence of outliers in the 'gps-height' feature.

2) Jason: Due to the presence of missing data in the Latitude & Longitude columns, Jason decided to apply mean imputation based on the Region column. The values of the Region column corresponds with the name of cities present in Tanzania. By calculating the mean latitude and longitude value of each region, a rough estimation of the geographical location of wells with missing value could be known.

During the Data Analysis Phase, he noticed the Permit and Public Meeting columns had missing values. Upon further inspection, these two columns only contain the values of either 'True' or 'False'. Data Imputation was not done here due to the lack of valuable data present in the data set. To preserve the distribution of these two columns, a unique values known as 'Unknown' was given to rows with missing data.

He performed data recategorisation on both funder and installer columns which contained 1000 - 2000 unique values.

He first performed data cleaning to fix spelling mistakes that were present in each column. This was followed by identifying unique values with count above the threshold of 1000. Each unique value above the previously mentioned threshold would be classified as its own individual class while those below it would be classified under the 'Other' value. Data recategorisation would be able to reduce the number of unique values present to improve the models' training perforamance.

Although the number of unique values in the Region Column were minimal, he decided to reclassify them according to their geographical zones based on data that was provided by the Tanzania Water and Sanitation Network [6]. This reduced the number of unique values of the Region Column to 7 from 21. New insights could potentially be drawn upon based on the zone that the water wells is currently located i.

The data set provided had feature and target variables in the form of categorical form. he had converted these features into numerical form that is required of by ML models prior to training. He had encoded the values of the feature and target variables in the form of alphabetical order whereby a = 0, b = 1 etc.

C. Data Classification

Initially, we focused on testing the performance of different algorithms without any feature selection. This allows us to focus on the best performing ones. See Table. I. We can see that XGBoostClassifier, CatBoostClassifier, BaggingClassifier & HistGradientBoostingClassifier were the most effective for our problem. We decided to explore these models using feature selection & hyper-parameter tuning. Our feature selection process employed a Chi-Squared test and feature importances obtained from a RandomForest and a XGBoost.

TABLE I: Initial Classification Results

Algorithm	Accuracy	Precision	Recall
XGB	**0.799**	**0.751**	0.633
CatBoost	0.795	0.746	0.634
Bagging	0.793	0.704	**0.659**
HistGradientBoosting	0.791	0.743	0.624
DT	0.757	0.643	0.645
KNN	0.709	0.623	0.563

1) Thomas: Thomas trained the 4 top models (XGBoost, CatBoost, Bagging & HGBoost) on the SMOTE balanced dataset and compared the results to models trained on the imbalanced dataset. The results were also compared when optimizing for 'recall_macro' or 'accuracy'. Recall is usually a better metric for imbalanced datasets, as accuracy can often misrepresent the truth. 'recall_macro' takes an average of the recall for all 3 classes, which makes it a good metric to use.

Furthermore, he used Weights and Biases (WandB) [7] to analyse the subset of features produced by the Chi-Squared Test and RandomForest. WandB served as an accesible MLOps platform for experiment tracking. Multiple classifiers were trained on different feature subsets (ranging from sizes 0.75N to N, where N is the size of the original feature set), and tracked this information in WandB. WandB allows us to quickly filter for the best performing 'runs', and the feature subset used. He also used WandB to further analyse the results of his cross-validation hyper-parameter tuning, in much a similar process to feature selection.

2) Jason: From the Random Forest feature importance and Chi-Squared Test, Jason had shortlisted 16 features that influenced the classification of Tanzanian Water Wells. Prior to model training, the dataset was subjected to a 80%:20% train test split. This was followed by normalising the testing and training set features with z-score normalisation.

For this study, he considered three different machine learning models (Random Forrest, XGBoost & CatBoost). Hyperparameter tuning was conducted via GridSearchCV [8] from the sklearn library. Upon completion of the hyperparameter tuning process, the most optimal parameters of each model were recorded before being passed for model training.

To evaluate the performance of each model, Jason used three different evaluation methods. K-fold cross validation with the value of K being 5 , confusion matrix and receiver operating characteristic (ROC) curve. K-fold cross validations was used to evaluate the performance of the model on unseen data. Meanwhile, confusion matrix showcases the predictions which are labelled correctly and incorrectly by class. Although ROC Curves are usually meant for binary classification, it was extended to be used for multiclass classification through pairwise comparison i.e., one class vs all other classes.

IV. Results

A. Data Analysis

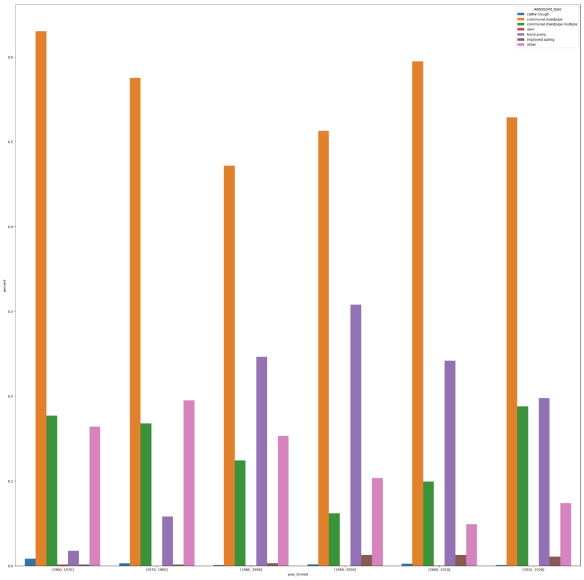
1) Thomas: An example of the construction year visulisations can be see in Fig. 3. From this, we can see that there is a slight variation in Waterpoint Type usage across decades, but nothing of significance. The same is true across the other visualisations produced (see the accompanying ipynb for more details). For this reason, the missing values in the Construction year were kept as 'Unknown'. The distribution of the status group values in 'Unknown' or 'Not Unknown' construction year values can be seen in Fig 3.

2) Jason: As stated in Section III Methodology, Jason analysed the distribution of missing and unique values across all 38 feature columns. One key highlight of this stage could be seen in Fig 4. This figure showcases the presence of a large number for a particular value in both latitude and longitude columns which would have to be taken note of before proceeding with model training. Furthermore, he had noticed that they were a number of columns that were representing the same thing such as Source & Source Type. This could be observed in Fig 5. Other visualisations could be seen in the ipynb notebook submitted with this report.

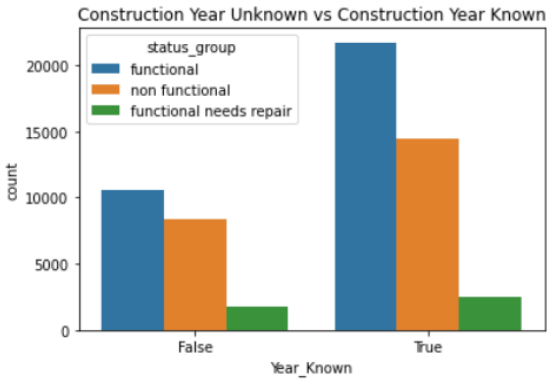
B. Data Preprocessing

1) Thomas: Firstly, The results of the latitude and longitude can be seen in Fig. 6.

The installer & funder columns were categorized manually using Thomas' own knowledge and online research. The result was 8 categories, the counts for these are presented in Table



(a) Waterpoint Type vs Construction Year



(b) Construction Year Unknown vs Construction Year Known

Fig. 3: Construction Year Data Analysis

```
----------latitude----------
-2.000000e-08    1812
-6.985842e+00       2
-6.980220e+00       2
-2.476680e+00       2
-6.978263e+00       2
                  ...
-3.287619e+00       1
-8.234989e+00       1
-3.268579e+00       1
-1.146053e+01       1
-6.747464e+00       1
Name: latitude, Length: 57517, dtype: int64
Missing Values of latitude column: 0
Unique Values of latitude column: 57517
```

(a) Longitude Distribution

```
----------longitude----------
0.000000     1812
37.375717       2
38.340501       2
39.086183       2
33.005032       2
               ...
35.885754       1
36.626541       1
37.333530       1
38.970078       1
38.104048       1
Name: longitude, Length: 57516, dtype: int64
Missing Values of longitude column: 0
Unique Values of longitude column: 57516
```

(b) Latitude Distribution

Fig. 4: Latitude & Longitude Distribution

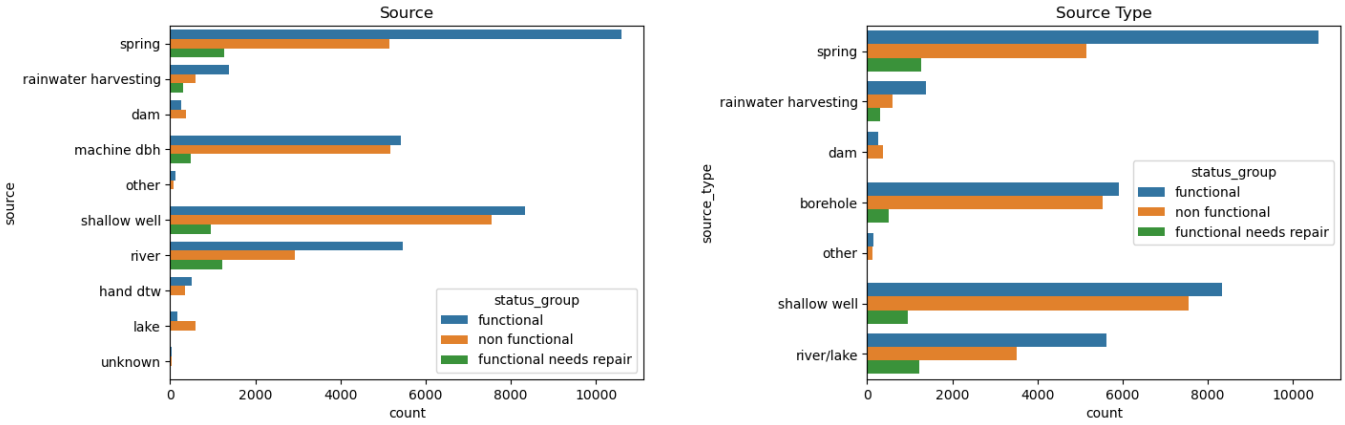
II. These versions of the features showed some benefit to the model when testing feature subsets in WandB

TABLE II: Funder & Installer Categories

Column	Category	Count
Funder	Government	20199
	Charity	11066
	Unknown	8216
	Foreign Aid	8131
	Religious	4087
	Private	3889
	Local Government	3774
	School	38
Installer	Local Government	22515
	Government	10327
	Unknown	8800
	Charity	7487
	Private	3853
	Foreign Aid	3346
	Religious	3046
	School	26

Thomas used the SMOTE-ENN algorithm to oversample the minority class. The results of this can be seen in Fig. 7. On the x-axis, O is 'Functional', '1' is 'Functional - Needs Repair' and 2 is 'Non-Functional'.

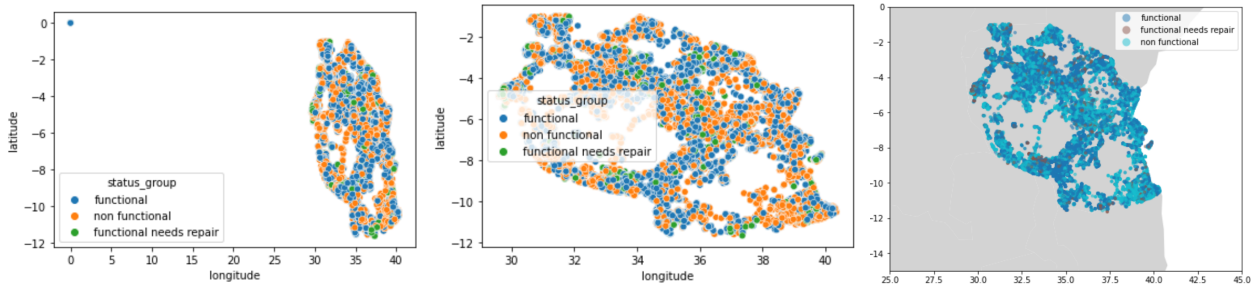
2) Jason: As mentioned previously , Jason had performed some pre-processing on the Longitude, Latitude, Public Meeting & Permit columns. Longitude & latitude was imputed with mean based on its assigned region. On the other hand, a new variable known as "Unknown" was used to classify rows with missing data in Public Meeting & Permit columns. Data reclassifications was also performed on funder, installer & Region Columns. For both funder & installer columns, he decided to classify unique values with values above 1000 as its own class while those with values lower than 1000 would be classified under "Other". The result of funder & installer columns reclassification could be seen in Table III. Jason utilised data provided by the Tanzanian Water and Sanitation Network to reduce the number of unique values in the Region Column. The graphical representation of the aforementioned pre-processing steps are represented in Fig .8



(a) Source Column Distribution

(b) Source Type Distribution

Fig. 5: Well Source Data Analysis

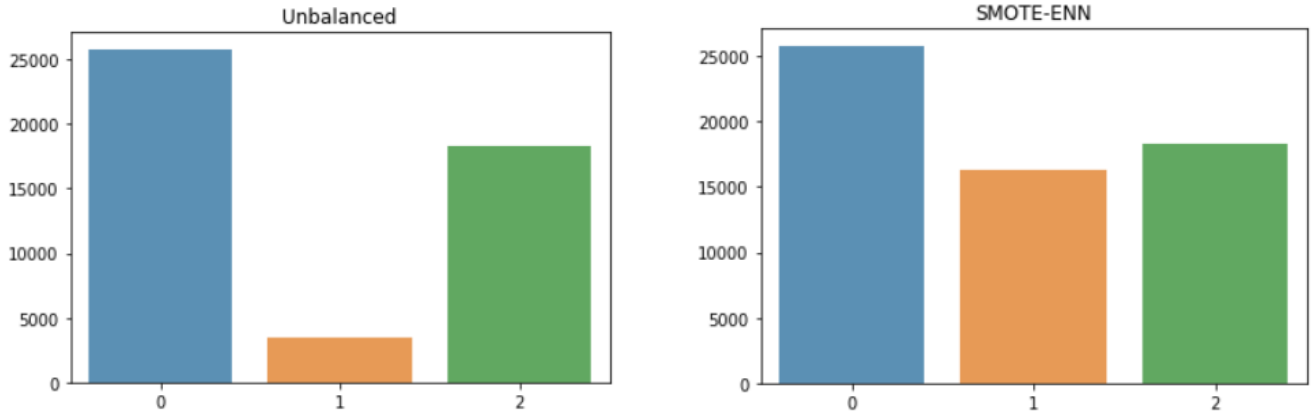


(a) Pre-Imputation Latitude & Longitude

(b) Post-Imputation Latitude & Longitude

(c) Imputated Latitude & Longitude Overlayed onto a map of Tanzania

Fig. 6: Latitude & Longitude Imputation



(a) Pre-Oversampling Class Distribution

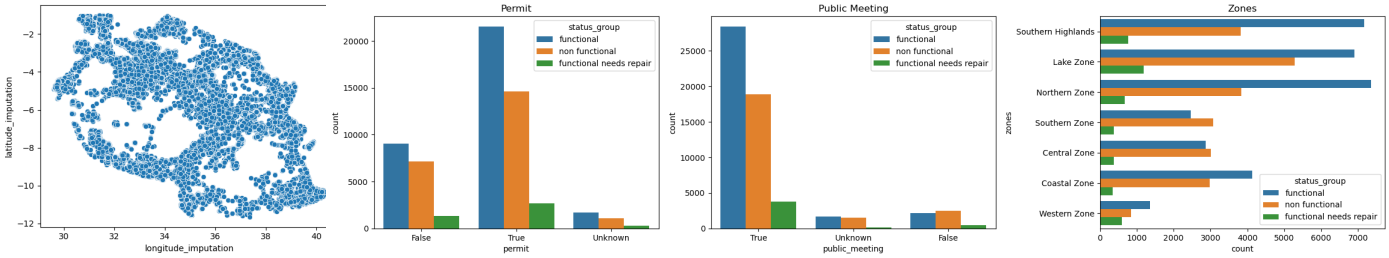
(b) Post-Oversampling Class Distribution

Fig. 7: SMOTE-ENN Oversampling

C. Classification

1) Thomas: Post hyper-parameter tuning,accuracy, precision ('macro'), recall ('macro') and f1-score were calculated for each of the models. The models were evaluated on the imbalanced and SMOTE-ENN balanced dataset. The results can be seen in Table IV

The results show the BaggingClassifiers performs the best, although the difference is minimal. The balanced dataset provides a slight increase in F1-Score, which accuracy is higher with the imbalanced dataset. This makes sense, as incorrectly classifying the minority class has a small impact on accuracy but a large impact on F1-Score.



(a) Latitude & Longitude Mean Imputation

(b) Permit Column After Handling Missing Values

(c) Public Meeting Column After Handling Missing Values

(d) Region Column Distribution After Recategorisation

Fig. 8: Results of Data Pre-processing

TABLE III: Funder & Installer Recategorise Values

Column	Category	Count
Funder	Other	37405
	Gov	9084
	Danida	3114
	Hesawa	2203
	ELCT	1540
	RWSSP	1381
	World Bank	1349
	World Vision	1246
	Unicef	1058
	District Council	1020
Installer	Other	31828
	DWE	17402
	Gov	3610
	Community	1745
	Hesawa	1395
	RWE	1206
	ELCT	1163
	Danida	1051

Thomas produced the two confusion matrices using an XGBoost, see Fig. 9. They show the output of training on both the balanced and imbalanced datasets. Balancing the dataset results in less False Positives on the minority class. If the goal of your model was to do specifically this, perhaps using the balanced dataset would be the best idea. This was not the case for us, so we continued with using the imbalanced dataset.

Since the difference between different models and datasets is neglible, Thomas decided to combine all the models to create a VotingClassifier to possibly squeeze out some extra performance. These results can be seen in Table V

TABLE V: Voting Classifier Results

Accuracy	Precision	Recall	F1-Score
0.810	0.759	0.650	0.679

Using both the results from model based feature selection, and feature selection after looking at the results from Weights & Biases, Thomas decided to use the following features in his final model: **'age'**, **'latitude_imputation'**, **'longitude_imputation'**, **'construction_decade'**, **'quality_group'**, **'basin'**, **'extraction_type'**, **'cat_installer'**, **'population'**, **'gps_height_zscorenormalise'**, **'cat_funder'**, **'quantity'**, **'consistent_water'**, **'source_class'**, **'zones'**, **'waterpoint_type'**, **'season'**, **'extraction_type_class'**, **'payment'** (Please consult the ipynb for more details on what information these features contain).

To relate this back to our research questions, we can say that these features are the most important when looking at whether wells are functional or not.We can also say we can classify whether a well is function or not with 81% accuracy.

2) Jason: Based on the results that were obtained from the random forest feature importance and Chi-Squared Test, Jason had decided to use the following features for his model: **'longitude_imputation'**, **'latitude_imputation'**, **'quantity'**, **'extraction_type_class'**, **'gps_height'**, **'age'**, **'waterpoint_type_group'**, **'population_original'**, **'payment_type'**, **'source_type'**, **'funder_groups'**, **'basin'**, **'installer_grouped'**, **'management'**, **'water_quality'**, **'public_meeting'**.

To evaluate the three models that Jason had trained, he decided to use K-fold cross validation with K having a value of 5 and the plotting of confusion matrices. Important metrics such as precision,recall & f1-score and K-fold cross validation accuracy score were also calculated. Precision,recall & f1-score were calculated using macro average. The results of this evaluation can be seen in Table VI.

TABLE VI: Trained Model Classification Results

Model	**Cross-val Accuracy**	**Precision**	**Recall**	**F1-Score**
Random Forrest	0.795	0.72	0.64	0.67
XGBoost	**0.800**	0.69	**0.67**	**0.68**
CatBoost	0.787	**0.73**	0.60	0.63

Receiver Operating Characteristic Curves (ROC) for each model were plotted and could be seen in Fig 10.

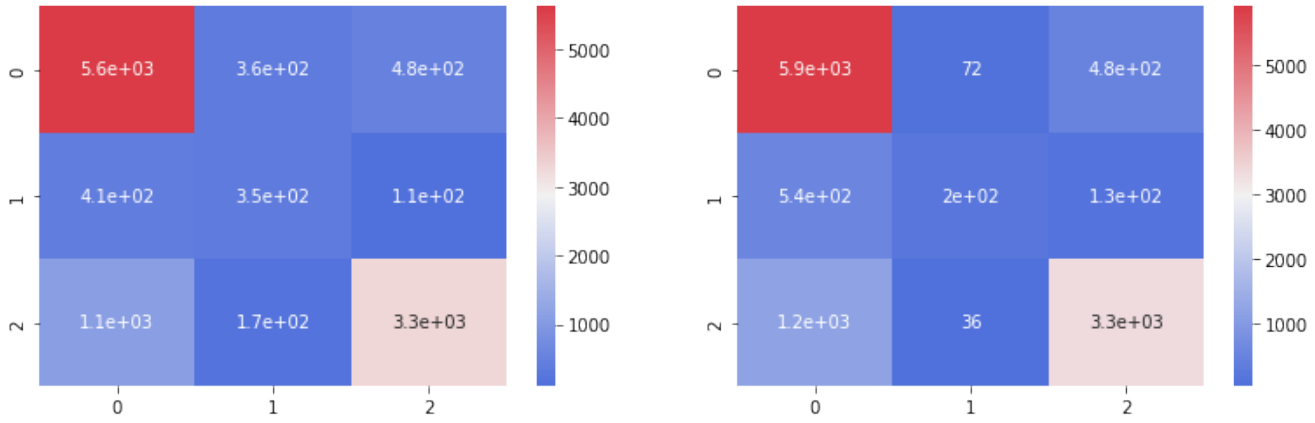
Out of the 3 models that I had trained throughout this study, I found out that XGBoost performed the best achieving an accuracy of 80% over Random Forrest (79.5%) and CatBoost (78.7%)

V. Discussion

In this section, we discuss the results of our analysis. We compare each of our separate approaches to each other, as well as comparing them to the performance of models in the literature.

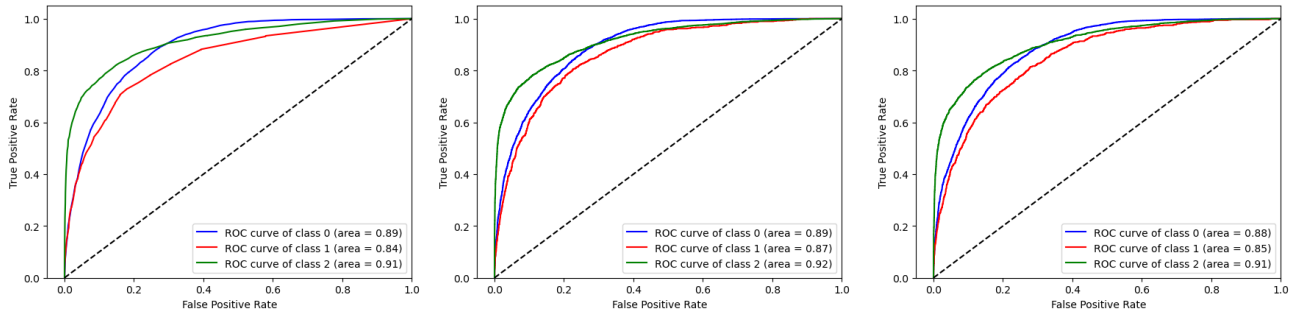
TABLE IV: Classification Results

Scoring	Dataset	Model	Accuracy	Precision	Recall	F1-Score
Recall Macro	Balanced	XGBoost	0.802	0.701	0.668	0.683
		CatBoost	0.783	0.669	0.660	0.664
		HistGradientBoosting	0.796	0.693	0.665	0.677
		BaggingClassifier	0.803	0.703	**0.676**	**0.687**
	Imbalanced	XGBoost	0.804	0.720	0.662	0.683
		CatBoost	0.791	0.697	0.652	0.668
		HistGradientBoosting	0.806	0.730	0.658	0.681
		BaggingClassifier	0.803	0.722	0.660	0.681
Accuracy	Balanced	XGBoost	0.800	0.700	0.662	0.677
		CatBoost	0.787	0.678	0.665	0.670
		HistGradientBoosting	0.797	0.699	0.666	0.680
		BaggingClassifier	0.801	0.701	0.671	0.684
	Imbalanced	XGBoost	0.804	**0.748**	0.648	0.676
		CatBoost	0.797	0.753	0.635	0.665
		HistGradientBoosting	0.806	0.733	0.662	0.686
		BaggingClassifier	**0.811**	0.741	0.656	0.681



(a) Balanced Dataset (b) Imbalanced Dataset

Fig. 9: Balanced vs Imbalanced Confusion Matrices (XGBoost)



(a) Random Forrest ROC Curve (b) XGBoost ROC Curve (c) CatBoost ROC Curve

Fig. 10: Models' ROC Curve

A. *Pre-Processing*

1) Tom: Jason and I used many different approaches throughout the project. For instance, Jason utilized a StandardScaler to scale every feature by removing the mean and scaling to a unit variance. I did not scale any features except 'gps_height', and even then I used a MinMaxScaler. Despite the presence of categorical data, Jason's method still produced high quality results. Another difference in pre-processing was the handling of the funder and installer columns. We both took different approaches to this, and in my opinion Jason's technique proved slightly better. By categorizing the entire dataset, valuable information was lost by not using the specific funders or installers. Jason's approached lost less information as only values with small counts were removed from the dataset and classified as 'Other'.

2) Jason: One of the differences that could be observed in the Pre-processing stage of this study is the way Thomas and I implemented mean imputation for the missing values in longitude & latitude columns. I decided to utilise a simpler approach where I imputed based on a region's average value. However, Tom decided to impute them based on the order of 'ward', 'lga' and 'region'. Tom's method in theory should represent the data distribution better as it takes more specific features such as 'ward' & 'lga' which are smaller than 'region'. The simpler approach that I took could skew the data towards the mean of a region which could result in some data being lost. But during model evaluation it was noted that the simpler approach resulted in better performance.

Another aspect that was different was the way that we performed data recategorisation on the funder and installer columns. I decided to first fix the spelling mistakes before proceeding to classifying those unique values with value counts above 1000 as its own individual class while those below that threshold would be classified under the "Other" class. Tom decided to individually classify them in categories based on his knowledge and online research. Initially, I felt that those unique values above 1000 should be their own category as they is large number of data samples whereby machine learning model can learn from. Those values less than 1000 should in theory not affect the model's training by much therefore classifying them as "Other" would be a safe option. By performing the recategorisation based on his own, Tom had a smaller number of categories than me at the cost of losing valuable information that could be obtained from unique values that were in large numbers.

Although both of us had applied different normalisation methods i.e. Tom applied MinMaxScaler , I applied Z-Score Normalisation, our models performed fairly way achieving accuracy of 81% and 80% respectively. This indicates that both normalisation methods could be considered acceptable in this study.

B. Modelling

1) Tom: We also used different hyper-parameter tuning methods, specifically GridSearch (Jason) and RandomSearch (Tom). RandomSearch enabled a wider exploration of hyperparameter ranges across various models, making it faster. On the other hand, GridSearch focused on specific potential hyperparameters, providing a more in-depth search. I think this is reflected in our results, as Jason's XGBoost slightly outperformed my XGBoost on the test set, however the breadth of search allowed me to find the BaggingClassifier, which performed very well.

2) Jason: Tom started by modelling baseline models involving different algorithms without feature selection to gauge the performance of each model on this dataset. This was in contrast what I did as I already had an idea on what models to develop. Tom's method actually gave a better insight on the models that could potentially be suited for this dataset. This allowed him to narrow down the models that he should try to developed. I noticed that rushing towards the development of a model directly without any testing like what I did was unwise as it could lead to valuable time being wasted on models that do not perform well on this dataset.

The choice of hyper-parameter tuning methods between the two of us showcased the different ideologies that we had. I opted for a smaller but in depth search space with Grid Search while Tom opted for a broad but shallower search space with Random Search. Compromises would have to made during hyper-parameter tuning, do we go for a more in depth but restricted search or a more broad but shallow search when improving model performance. Both approaches were able to achieve commendable results with Tom's Bagging Classifier slightly edging Jason's XGBoost in terms of accuracy (81% vs 80%)

When we consider the models that both of us had trained, I find Tom's implementation of a Bagging Classifer rather interesting. Instead of developing a model that utilised only one algorithm, he decided to combine his developed XGBoost, CatBoost and HistGradientBoosting into a voting classifier. All three models were used to make predictions on unseen data and the algorithm that had the best performance would be selected to make the classification. A Bagging Classifier in this scenario could be seen as more robust in comparison with models that only utilise one algorithm. The results from this study further echo the above sentiment with Tom's Bagging Classifier achieving better performance than my XGBoost.

C. Literature Discussion

When comparing to the TabNet implementation by Pathak et al [1], we can see that our best classifiers were outperformed by TabNet by at least 2%. This is quite significant. It's understandable that this is the case due to the capabilities of Transformers, which are arguably the most popular model right now.

We also reviewed Pham et al [2] and found that their produced Neural Network (NN) was not as high performing as some more lightweight models. XGBoost / HistGradientBoost and BaggingClassifier all out-perform the NN. These lightweight models also are much faster to train than an NN, so it is much more efficient to use these models on a dataset such as Pump It Up.

Upon comparison with the findings obtained from Jithin Paul [3] with ours, we observed that his Random Forrest Classier had surpassed our Bagging Classifier by a fine margin of 0.008%. This slight increase in terms of accuracy could be seen due to the number of features that was used for model training. Specifically, Paul had utilised 25 features while only 19 features were considered in our study. With a larger number of features, it could be theorise that machine learning models would be able to extract insights better leading to better classification performance.

VI. Conclusion

Overall, we have successfully developed and evaluated 7 different ML models on the Pump It Up dataset. Tom's Bagging Classifier performed the best with a classification

accuracy of 81%. Our models have showcased that it is feasible for ML models to aid the Tanzanian Government in classifying the status of wells based on historical data. With machine learning, the Tanzanian Government would be able to act quicker in repairing wells that are non functional for the benefit of their people. One of the shortcomings in this study is that the dataset provided was incomplete and had invalid values. Important values such as construction year which would typically affect the status of a well was missing in the regions of 20,000s. Although imputation was done to mitigate the effects of invalid data, it is still not a proper representation of the data that the ML would be facing with during deployment.

However, one of our supplementary research questions: **Could we use our results to ensure that the wells are built and repaired so that fewer wells are non functional?** was not answered in this study due to the lack of relevant data in the Pump It Up dataset. Moving forward, we seek to obtain additional data from Taarifa and Tanzanian Ministry of Water to be able to calculate the lifetime and decay rate of wells as mentioned by Pham et al [2]. Both of these metrics would allow us to have a better understanding of the lifetime of a well and how long it takes for a well to be non functional. Furthermore, we could explore the possibility of applying more state of the art ML models i.e. Transformers on the Pump It Up dataset as only traditional ML models were applied in this study.

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