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TECHNICAL ARTICLE

Intelligent Mine Water Management Tools—*e*Metsi and Machine Learning GUI

Kagiso Samuel More[1] · **Christian Wolkersdorfer**[1]

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Abstract

Digital technologies have helped ensure that mining-influenced water (MIW) is treated and managed effectively in water treatment plants. This paper presents two new intelligent mine water management (iMineWa) tools, *e*Metsi, and a machine learning graphical user interface (ML-GUI), to help improve practices in mine water treatment plants. *e*Metsi, which means electronic water in Setswana language, is a framework that uses near-field communication (NFC) technology in conjunction with mobile and website applications in mine water sampling. It incorporates application of NFC microchips to sampling bottles, usage of mobile application for recording on-site data during sampling, and website application for data display and storage. *e*Metsi enables fast data communication between the samplers, laboratory technicians, and client, and thus helps users to attain sampling and sample analysis targets. ML-GUI is an artificial intelligence-driven user interface that can be used to build predictive models. Even mine water treatment plant operators without programming experience can use ML-GUI to build ML models, which they can use to perform forecasting analysis to plan what chemicals and methods they need to use to manage MIW. Finally, *e*Metsi and ML-GUI could potentially also be used in other industries such as municipal waste water treatment plants, water resource management, and agriculture.

Keywords Digital technologies · Mobile application · Website application · Near-field communication · Data modelling software

Introduction and Background

Intelligent mine water management (iMineWa) refers to the application of modern digital technologies, e.g. wireless sensor networks, internet of things (IoT), big data analytics, and cloud computing to name a few, to "smartly" manage mining-influenced water (MIW; More et al. 2020). Wolkersdorfer (2013) introduced the term internet of mine water or IoMW to describe a platform that integrates technologies on a mine site. This study presents two iMineWa tools that form part of the IoMW: an *e*-tag-based mine water evaluation, testing, sampling, and identification application (*e*Metsi) and a machine learning graphical user interface (ML-GUI). Developing a complete IoMW will take several years, so this paper presents the initial steps of some ongoing work. Some of the technologies that will form part of a complete IoMW framework will be integrated in the *e*Metsi and ML-GUI applications.

*e*Metsi, which means electronic water in Setswana language, is a framework for radio-frequency identification (RFID) technology that can be used in conjunction with mobile and website applications in mine water sampling. RFID is the wireless contactless technology that uses radiated and reflected radio frequency waves to transfer data. The *e*Metsi application is the first of its kind in the mine water sector. Embedding items with RFID microchips enables users to identify and track the items (Finkenzeller 2010; Shepard 2005). The type of RFID technology used in the *e*Metsi application is referred to as near-field communication (NFC) technology. A typical NFC system is made up of an active NFC device, a passive NFC device, and a mobile application or a host computer (Fig. 1; Coskun et al. 2013; Silva-Pedroza et al. 2017).

✉ Christian Wolkersdorfer
Christian@Wolkersdorfer.info

Kagiso Samuel More
kagiso@moredatabytes.tech

[1] SARChI Chair for Mine Water Management, Department of Environmental, Water and Earth Sciences, Tshwane University of Technology, Private Bag X680, Pretoria 0001, South Africa

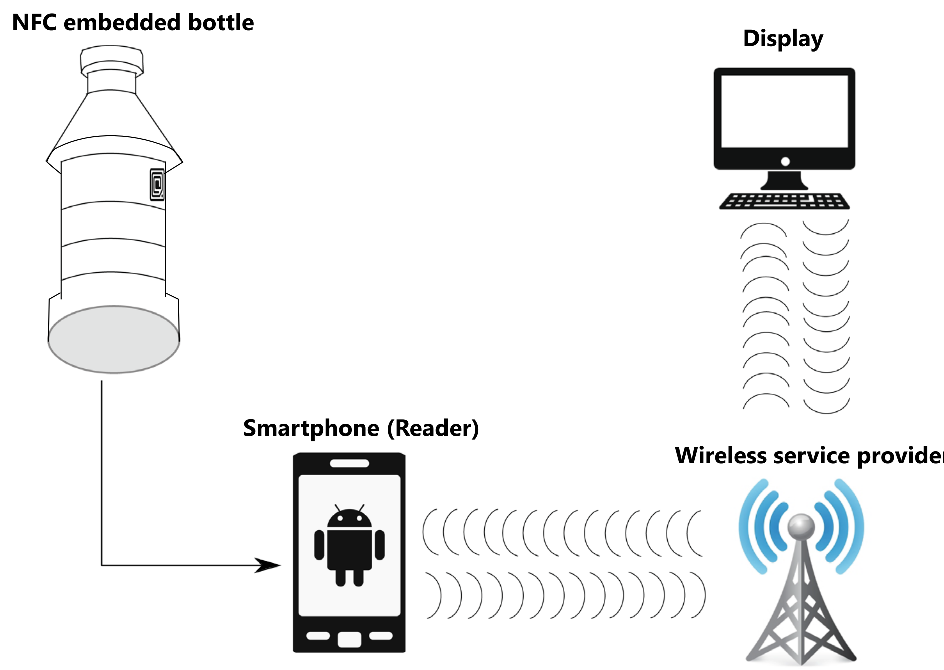

Fig. 1 NFC application structure

*e*Metsi consists of identifying the samples electronically at the time of sampling using sampling bottles embedded with NFC microchips, storing the on-site parameters and sample data, and transferring the data to a cloud storage location, which allows the end-users to access the sample identifying data. This closes the gap between the sampler, laboratory, and sampling institution, i.e. enabling the sharing of sampling parameters and results, sampling times, and locations in real-time to reduce errors. The mining industry (and many other industries) still widely uses hand labelled or barcoded sample containers for identification and tracking purposes, but this can lead to errors when samples and sampling locations are mixed up or labels become unreadable. In addition, there is currently no direct communication between the sampling site, laboratory information management system, and sampling institution. This slows down the exchange of data and can cause problems in regulating the water treatment plant's parameters.

Several languages were used to carry out the *e*Metsi framework, including extensible mark-up language (XML) and Java code for the Android mobile application, and cascading style sheets 3 (CSS3), hyper-text mark-up language 5 (HTML5), and JavaScript programming for the website application. The applications also required server provisioning and structured query language (SQL) configuration to ensure maximal flexibility of the system.

Another iMineWa tool introduced in this study is ML-GUI, which is an interface that enables users to build predictive machine learning (ML) models. Predictive ML models are used in mine water treatment plants to forecast the chemistry of MIW, thereby enabling treatment plant operators to plan what chemicals and methods to use to manage polluted MIW (e.g. More and Wolkersdorfer 2022). Not every worker in a treatment plant (or any other working environment) can write program code. Thus, the purpose for the development of the GUI is to ensure that data are easily processed and analysed without having to write these codes. The GUI can perform several functions such as loading a CSV file, data pre-processing such as normalisation using different scaling options (i.e. robust, standard, Min/Max scalers, and power transformer) and data visualisation (i.e. scatter plots, histograms, and heat maps). Additionally, the GUI is embedded with several ML algorithms (i.e. gradient boosting regression tree, random forest regression tree, and linear regression; Fig. 2). In a few clicks, data can be loaded, visualised, pre-processed, and ML models quickly built without having to write the associated code.

Python 3.7.1 was used to develop the ML-GUI using several frameworks and libraries. The core tools used in the development of the ML-GUI are the PyQt 5.9.2 and Qt designer frameworks (Harwani 2011; Rempt 2001). For this study, the GUI was designed using Qt designer, and its pages were linked and programmed using Python via the PyQt package. In addition, the Pyinstaller 4.8 library was used to convert the Python files to executables. Furthermore, InstallForge 1.4.2 was used to combine the files Pyinstaller created into a single file installer. This enabled the developed GUI to be used in any Windows-powered machine.

The IoMW is a platform that comprises several digital technologies such as artificial intelligence (AI), IoT, cloud computing, big data analytics, and sensor networks. This paper only presents a portion of the IoMW platform and

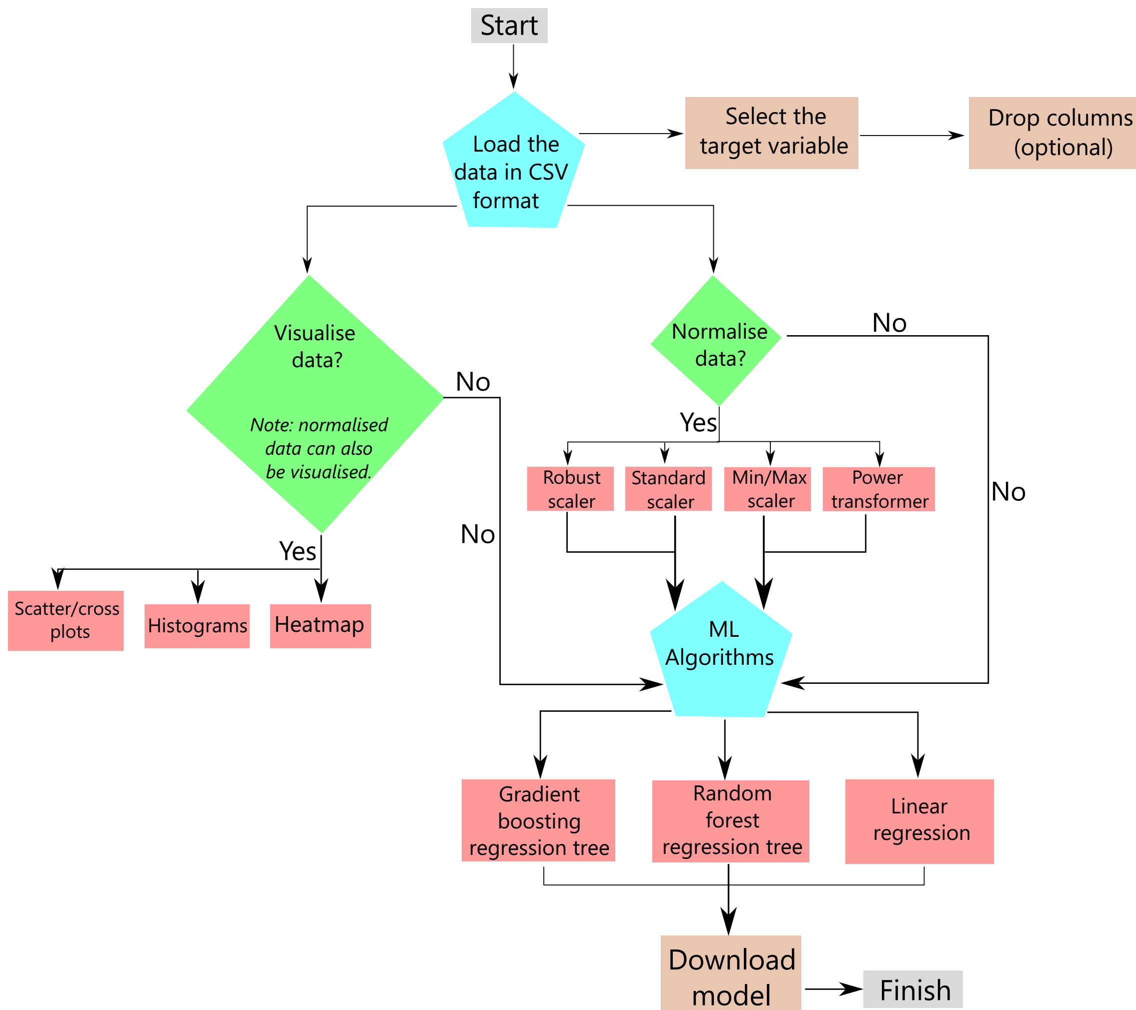

Fig. 2 The ML-GUI user guide flow chart

uses AI in the form of ML-GUI, IoT, and cloud technology through the *e*Metsi application. In addition, IoMW is a useful platform that is adaptable for any treatment plant, including municipal waste water treatment plants.

Related Work

Industries can reduce operational costs and save time by applying data collection systems that are supported by RFID technology (Demiralp et al. 2012). Manufacturing, healthcare, agriculture, and logistics industries, to name a few, are widely using RFID technology to perform tasks such as ID badging, asset tracking, access control, inventory management, and personnel tracking (e.g. Kumari et al. 2015; Ngai et al. 2007; Wang et al. 2010; Zhu et al. 2012). RFID technology is also used in the retail sector through item level inventory tracking by tracking items from the supply chain to sale. In athletics, race participants (e.g. in marathons) are tracked and timed using RFID technology. Mahdin et al. (2017) used RFID together with sensor technology to monitor water levels in household water tanks; if the water level falls below the required threshold, a mobile phone is notified. The use of RFID technology in conjunction with cloud storage, mobile, and website applications for mine water sampling is unique to this study. Others have used artificial intelligence (AI) and dynamic modelling approaches to forecast water chemistry (e.g. Ekemen Keskin et al. 2020; Hrnjica and Bonacci 2019; Rooki et al. 2011; Sakizadeh 2015; Singh et al. 2017). However, these approaches cannot be applied by everyone working in a treatment plant. ML-GUI ensures that all the programming and coding work is put in a user interface that plant operators will find easy to use. Thus, ML-GUI will help plant operators to explore data, build predictive models, and ultimately upskill themselves.

Intelligent Mine Water Management Tools

Electronic Tracking and Identification of Mine Water Samples and Sampling Results (eMetsi)

Currently, when mine water samples are collected, there is no direct communication between the samplers, the laboratory, and the sampling institution. This slows down data exchange and can result in high response times for regulating the treatment plant's parameters. In addition, samples can easily get interchanged when being taken from the sampling site to the laboratory and data can be misplaced or lost. *e*Metsi aims to close the gap between the sampler, laboratory, and sampling institution through real-time data exchange. In the development of the *e*Metsi framework, an NFC microchip was incorporated on mine water sampling bottles during the sampling and testing process. The NFC microchips used in this study are high frequency (HF) spectrum chips with a primary frequency range of 13.56 MHz, a communication distance of up to 30 mm, and a circular shape, with a diameter of 10 mm (Microsensys, GmbH, Erfurt, Germany; Fig. 3). HF spectra are a type of RFID frequency bands that are normally used in gaming chips, personal ID cards, library books, and NFC applications (e.g. Chang et al. 2010; Ching and Tai 2009; Cho et al. 2013; Silva-Pedroza et al. 2017).

Several industries have explored ways of embedding electronic identification microchips on bottles for tracking, identification, or both. The *e*Metsi framework is unique as it incorporates NFC microchips into the sampling bottles, uses an NFC mobile application for recording on-site data during sampling, and a website application for data display and storage (Fig. 4). Therefore, *e*Metsi is a combination of IoT, RFID, and cloud storage technologies, and has the potential to incorporate big data analytics in its framework. Based on literature reviews, merging the aforementioned technologies has never been done before for mine water management related studies.

Machine Learning Graphical User Interface

The GUI was developed using the Python programming language and a Qt designer within an Anaconda platform and is entitled "The Internet of Mine Water". Several Python libraries are part of the GUI: Matplotlib, Seaborn, Numpy, Pandas, Scikit-learn, Pickle, and PyQt5 were used to write Python scripts in the Spyder integrated development environment (IDE) software, while Pyinstaller was used to build the Python files into an executable file. Qt designer was used to design the GUI pages and CSS was applied for styling these pages. Pyinstaller library files were compiled into a single installer file using InstallForge. ML-GUI was built to be compatible for any Windows operating system, has an End-User license agreement, and requires 1.14 GB of space.

Evaluation and Advantages of the Tools

eMetsi

*e*Metsi identifies samples at the sampling site and the laboratory, thereby reducing errors in exchanging data relevant to the sample and the laboratory results. Additionally, recording all sample data manually (e.g. on sampling sheets, field books, notebooks, or field computers) or without using a relational database management system (e.g. MySQL, PostgreSQL, or Microsoft SQL Server) can be time consuming and inconvenient. With *e*Metsi, sample parameters are recorded and accessed using mobile applications.

Fig. 3 NFC microchips and water sampling bottles used for the testing within the *e*Metsi study

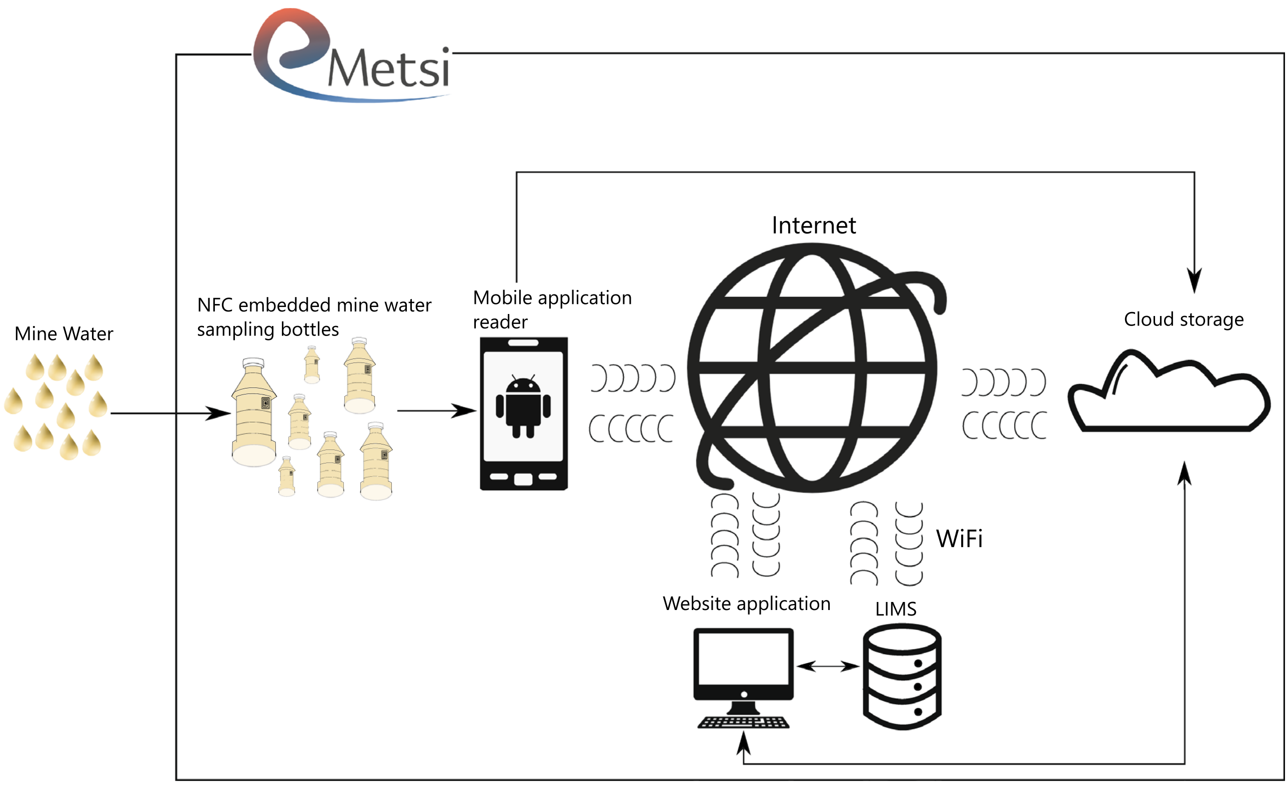

Fig. 4 *e*Metsi structure

*e*Metsi is not solely restricted to mine water samples but can be extended to samples taken in other environments (e.g. manufacturing, extra-terrestrial expeditions, life science, and agriculture). Furthermore, *e*Metsi also comes with the ability to store various types of data in different storage locations within the website application, which is highly beneficial. The data can include physico-chemical parameters (including water temperature, pH, redox potential, and electrical conductivity) written into the memory at various sampling location points, providing users with detailed and readily accessible sample field data.

AI-driven GUI

ML-GUI allows the user to load CSV files and has three regression ML algorithms embedded in it (gradient boosting regression tree, random forest regression tree, and linear regression). These algorithms can be used to build the models with the loaded data and the models can be downloaded and used for predictive analysis. To use the software, the user must first load the CSV file, select the target variable and drop any columns that are not needed to build the models (dropping of columns is optional). They then have the option to visualise the data by plotting scatter or cross plots, histograms, and heat maps using a Pearson correlation matrix, and/or normalise the data using different normalising techniques including robust, min/max, standard scalers, and power transformer. The user can then select a ML algorithm to build the model (Fig. 2). Plant operators can then use the developed GUI to optimise the management processes, though predictive modelling may be a complex topic for some plant operators. Therefore, information such as the selection of hyper-parameters for each algorithm and the evaluation metrics, for example the mean squared error (MSE) and mean absolute error (MAE) to understand the performance of the algorithm, should be shared by the employer with the plant operators so that errors are not made in selecting the best performing model on the supplied data.

Results and Discussions

NFC Mobile Application

*e*Metsi works on NFC-supported devices on the Android platform such as smartphones and field tablet. It can be used by anyone involved in a sampling project; in this case, the sampler, laboratory technician, and end-user of the results, and it includes a user management system. The mobile application has several functionalities, such as allowing the sampler and laboratory technician to write data back to the database. It also enables the end-user to view only the data that is on the database. In addition, the application can be used offline; however, a user management system is required in this instance. Furthermore, it is connected to a website application with data that is added using the mobile application, either pushed to the server and/or viewed using the website application.

The *e*Metsi mobile application has a satellite-based location feature (e.g. GPS) and an Open Street Maps functionality, enabling the user to pin the sampling location for every sampling point. It was developed using XML for defining layouts and Java code to provide processing logic. The mixture of XML and Java is widely used for Android application development. Layouts only declare the appearance of the application, which is then carried out by XML. Java code is used to define what the application must do. The *e*Metsi mobile application enables the user to navigate through multiple screens while recording and storing sampling data. Additional details and figures (Fig. S1) are provided for potential users as supplemental files that accompany the on-line version of this paper.

Website Application

The *e*Metsi framework also has a website application that can be accessed via an internet browser using an electronic device (e.g. a computer). It was created using CSS3 to add the look and style of webpages, HTML5 to structure the webpages and their contents, and JavaScript programming, which enables users to interact with the webpages. Data stored on the mobile application is pushed to the server and can be viewed on the website application. For this study, the *e*Metsi application was run on MySQL native drive for PHP (mysqlnd) 7.4.30. It should be noted that the application can be built using different relational database servers, i.e. any organisation willing to use *e*Metsi for their sample management can use their own server to store their data. Applying a user management system, the application can be used by five different user types, each having access to different webpages with different functionalities (Table 1).

At the beginning, the website requires login details that can be created by the administrator for everyone using it. The administrator controls the data that goes into the relational database server, the locations, and other users (Fig. 5). The project leader can add or view parameters that need to be analysed. Sampling personnel can view or add on-site field data and locations, while the laboratory technician and the client have limited functions, with the laboratory technician only able to view sample data and view or add parameters. The client can only see each data point and where the data came from (see supplemental Fig. S2). The laboratory technician and the client can only see the data that has been approved by the administrator.

Table 1 *e*Metsi website application's webpages and their functionalities for each user

User type	Webpages	Functionality
Administrator	Data	Read-only all data
	Available parameters	Read/write parameters used for analysis
	Requested parameters	Read/write parameters to be analysed
	View parameters	Read-only parameters
	Users	Read/write users
	Add new user	Read/write users
	Locations	Read/write locations
	Add new location	Read/write locations
Project leader	Data	Read-only all data
	Requested parameters	Read/write parameters to be analysed
	Available parameters	Read/write parameters used for analysis
	View request	View parameters to be analysed
	View parameters	Read-only parameters
Sampler	Data	Read/write sample data
	Locations	Read/write locations
	View parameters	Read-only parameters
Laboratory technician	Data	Read-only sample data
	View parameters	Read/write parameters
Client	Data	Read-only all data
	View parameters	Read-only parameters

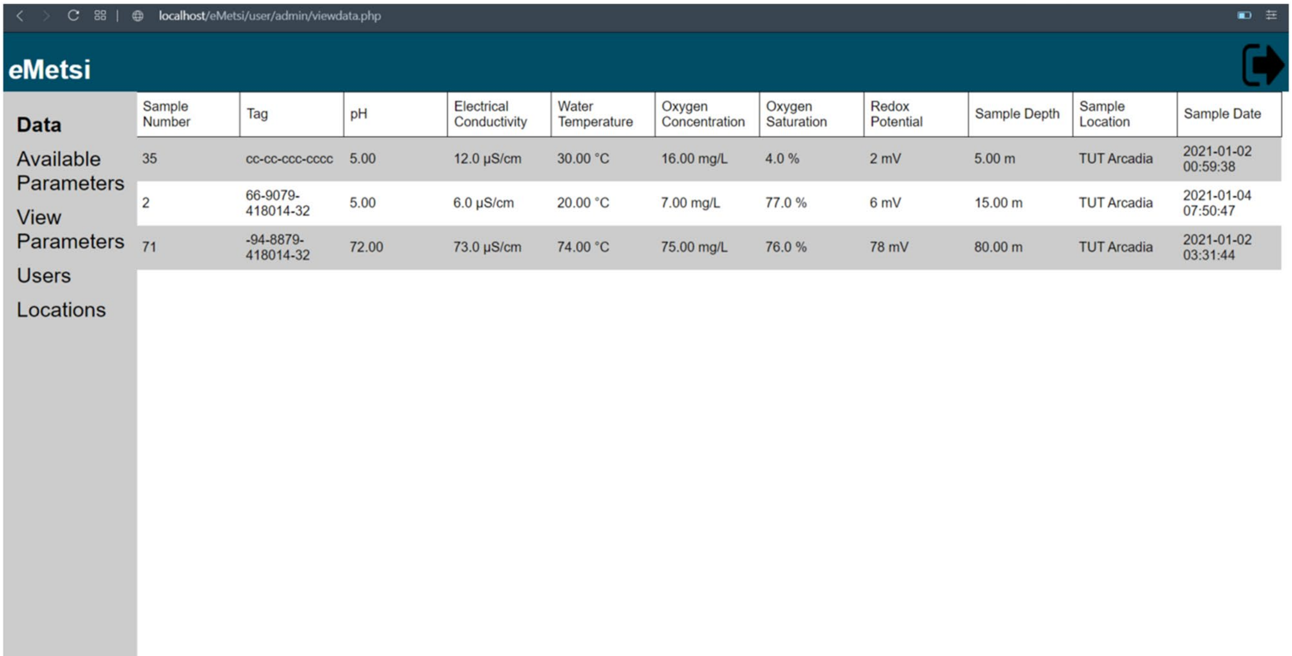

Fig. 5 A sample of the administrator's webpage (example data were used to test the website application)

GUI

Data pre-processing, visualisation, and building of ML models are key functions available to the user on the ML-GUI main window. In this platform, data can be pre-processed by dropping columns that are not needed to build the models and applying normalisation techniques such as robust, standard, min/max scalers or power transformation. ML-GUI also helps the user to visualise the data before building ML models. In this part, the user can plot scatter or cross plots (Fig. 6), histograms, or a heat maps. Cross plots show one variable on the *x*-axis and the other on the *y*-axis, histograms show the probability on the *y*-axis, and heat maps create a Pearson's correlation matrix with coefficient correlations (*r*).

The ML-GUI application has three embedded machine learning algorithms: a gradient boosting regression tree, a random forest regression tree, and linear regression (Fig. 7). When the user clicks on one of the algorithms and chooses to train the data by clicking "Train", a new window will open. In the new window, the user is able to tune the ML algorithm hyper-parameters such as number of trees and learning rate, and the user also has an option to set the test size. Once the user is done training the algorithm, the model performance (MAE, MSE and root mean squared error) will show. If the user is satisfied with the performance, the model can be downloaded. Once the user has new data, the model can be used in Python to perform predictive analysis. ML-GUI has already been tested by the authors to process data for selected South African mine water treatment plants in the West and East Rand. In future versions of this application, it is envisaged that the user might be able to perform predictive analysis without having to download files.

Conclusions and Future Work

A complete IoMW framework is made up of a variety of technologies, such as big data analytics, AI, wireless sensor networks (WSNs), an internet of things (IoT), 5G networks, and quantum computing. The iMineWa tools presented in this paper form part of a complete IoMW framework: *e*Metsi is based on the IoT, NFC, and cloud computing technologies, and AI technology drives the ML-GUI. For future work, *e*Metsi will be upgraded to enable integration with big data analytics in its system and all the IoMW technologies will be linked together to create one big framework. For example, WSNs will transfer data to the *e*Metsi application and ML-GUI will use that data to build predictive models. Data collected over the years by the WSNs will result in big data stored through the *e*Metsi

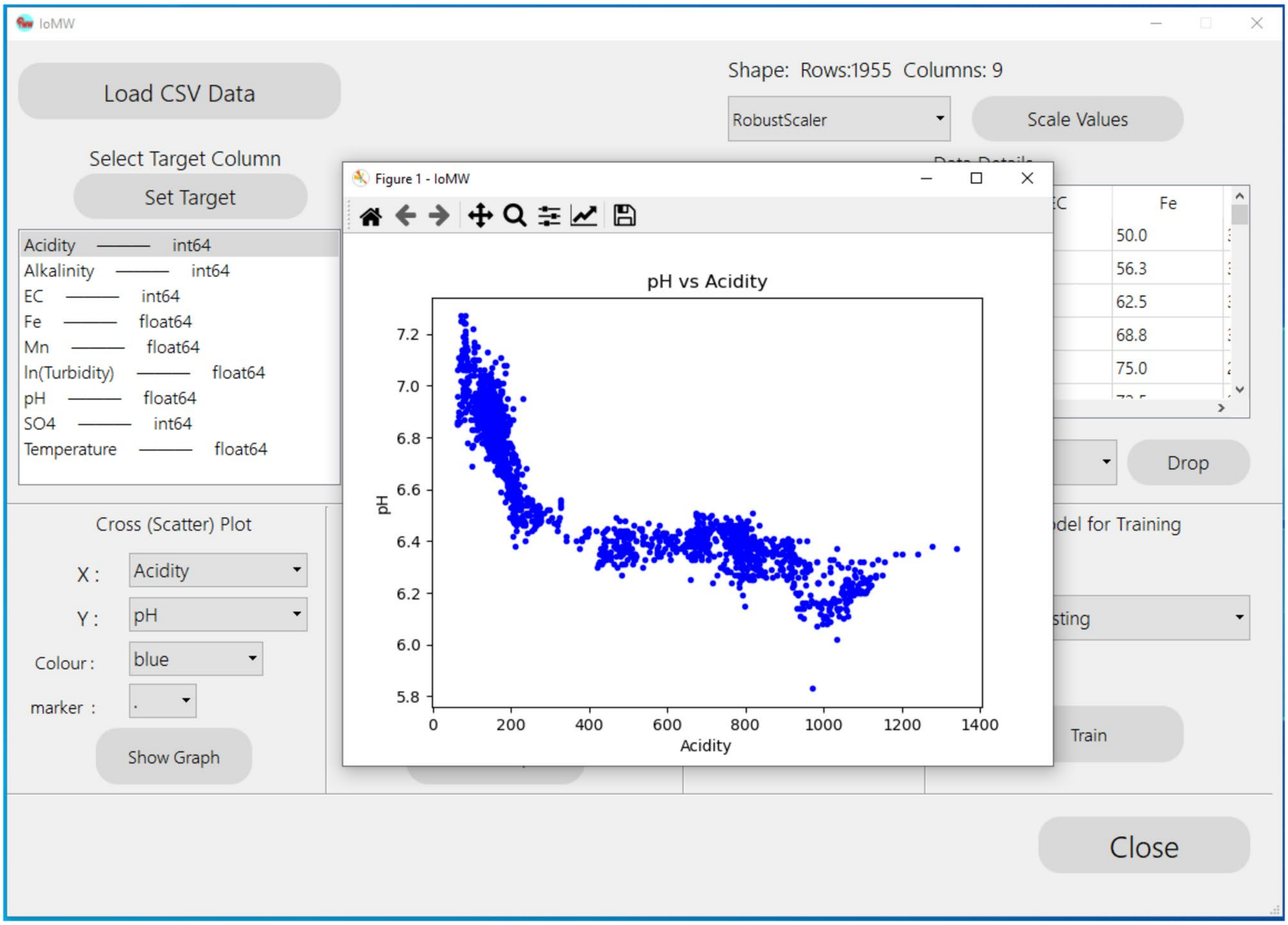

Fig. 6 Cross plots on the ML-GUI platform

application and ML-GUI will be used for data modelling and make good business decisions. More algorithms will be added to the ML-GUI so it can model different and complex data sets. In conclusion, this study showed that IoMW is a possibility as AI and IoT technologies were explored to find better ways of managing mine water. Making use of the latest digital technologies for mine water management yields positive outcomes such as real-time data communication, MIW chemistry forecasting and increased optimisation practices.

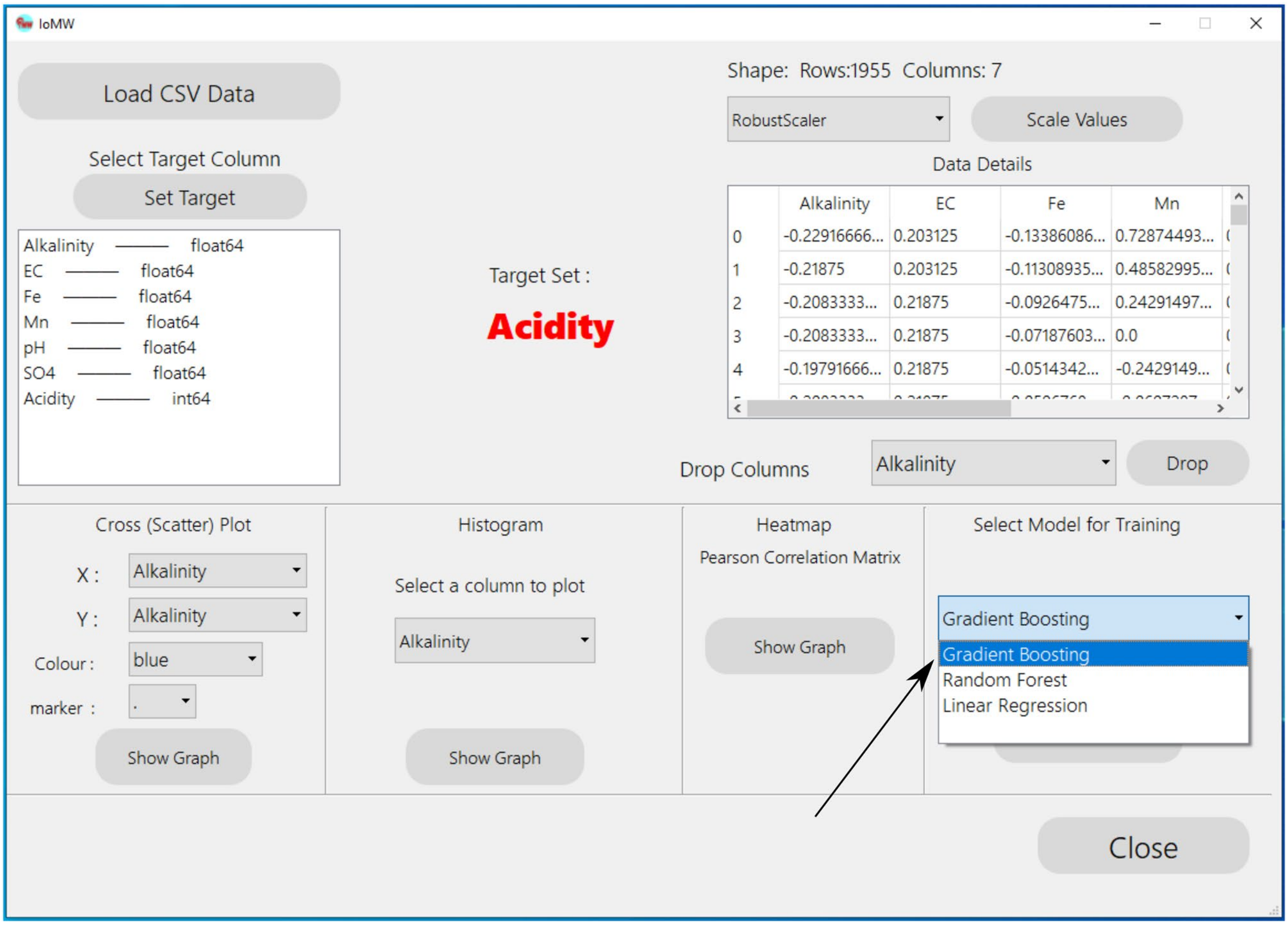

Fig. 7 ML-GUI with the algorithms indicated by the arrow

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10230-023-00917-7.

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Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

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