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Achieving Unprecedented Precision in Multiphase Flow Meter Monitoring with Deep Learning-Driven Abnormality Detection

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Abstract: In the oil and gas industry, multiphase flow meters are vital for simultaneous measurement of oil, gas, and water flow rates, yet their accuracy is often compromised by various abnormalities. This study introduces a pioneering solution, a deep learning-based abnormality detection method employing a recurrent neural network (RNN). Motivated by the need to enhance the reliability of multiphase flow meter readings and facilitate more efficient maintenance and repair processes, the research method involves training and testing the RNN model with historical data. The results showcase the RNN model's exceptional accuracy of 99.48%, an F1-score of 99.48%, and a recall of 99.48% post-troubleshooting. This heightened precision empowers the monitoring of multiphase flow meters, enabling swift identification and repair of abnormalities, ultimately preventing costly downtime in the oil and gas industry. Beyond its immediate applications, the study underscores the broader potential of advanced machine learning techniques to elevate the accuracy and reliability of multiphase flow meter measurements, presenting opportunities for widespread industry adoption.

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1. Introduction

In the oil and gas industry, the pivotal role of multiphase flow meters in gauging the flow rates of oil, gas, and water within pipelines is undisputed. The accuracy and reliability of these measurements are critical for optimizing production efficiency and ensuring operational safety. However, the susceptibility of flow meters to faults, including sensor drift, fouling, and component failures, poses significant challenges, leading to inaccurate readings and substantial downtime. Swift identification and rectification of these faults are imperative to uphold the precision and dependability of multiphase flow measurements.

This research emerges against traditional fault detection methods, relying on rule-based approaches fraught with unreliability and complexity. To address this, there has been a burgeoning interest in harnessing the power of machine learning techniques, particularly the application of deep learning models like the recurrent neural network (RNN) [1]. These models exhibit promising capabilities in detecting abnormalities in multiphase flow meter data, leveraging their aptitude for capturing temporal dependencies in time-series data.

The primary problem addressed by this study lies in the inefficiencies of traditional fault detection methods, necessitating a shift towards more advanced and practical approaches. Therefore, this research aims to propose a deep learning-based abnormality detection method using the RNN model to enhance the accuracy and reliability of multiphase flow meter measurements.

The scope of this study encompasses developing and evaluating the RNN model for abnormality detection, utilizing real-world flow meter data. The research methodology involves training and testing the RNN model on historical data to learn and identify deviations from expected behaviour, ultimately contributing to a more efficient maintenance and repair process within the oil and gas industry.

In summary, this research aims to bridge the gap in fault detection methods for multiphase flow meters, leveraging advanced machine learning techniques to improve accuracy and reliability significantly. The subsequent sections delve into the intricacies of the proposed RNN-based abnormality detection method, its implementation, and the empirical evidence supporting its efficacy.

2. Related Works

Previous research has investigated various aspects of the topic, ranging from theoretical underpinnings to practical applications. This section reviews relevant literature to comprehensively understand the field's current state. Specifically, we focus on studies exploring the oil and gas industry, and machine learning directly relates to our research question. By synthesizing these works, we aim to identify gaps in the existing knowledge and highlight opportunities for future research.

Various studies have focused on improving flow management, diagnostic tools, and measuring techniques in oil and gas production. Flow management for frac plug drill-out and flow back has been the subject of recent research [2]. Studies have also identified a decline in the well productivity index due to wellbore damage [3] and used numerical well-testing models to handle complex dual-porosity dual-permeability reservoirs [4]. A novel method and device for online multiphase flow detection based on magnetic resonance has been proposed by Deng et. al. in 2020 [5], while a study has shown that measuring mixture sound speed downhole can optimize multiphase flow meter systems [6]. Another study highlights the need to consider input parameter uncertainties when evaluating Venturi flow meter's performance [7]. A new flowrate out sensor design that requires little maintenance has also been developed by Cayeux in 2020 [8]. Yudin et. al. have developed a method for calculating pressure distribution in wellbores and pipelines by accounting for unsteadiness in multiphase flow [9]. Maru et. al. have tackled flow management using diagnostic techniques, optimization tools, and a new mixing system [10]. Fløisand et. al. have also significantly contributed [11].

In other areas of research, Yonel et. al. have presented a deep learning framework for synthetic aperture radar (SAR) imaging [12], while Çavdar et. al. have proposed a hybrid model of energy disaggregation for non-intrusive load monitoring [13]. Alom et. al. briefly survey advances in deep learning, focusing on deep neural networks [14]. Kim et. al. have evaluated a new MRI reconstruction method named LORAKI [15], and Jo et. al. studied deep learning in Alzheimer's disease using neuroimaging data [16]. Lee et. al. have proposed a new deep learning method for video rain removal using a recurrent neural network (RNN) architecture [17], and Zhou et. al. have investigated learning-based MIMO-OFDM symbol detection strategies using a special RNN called reservoir computing (RC) [18]. Priyasad et. al. have presented a deep learning-based approach to emotion classification using text and acoustic data [19]. Kollias et. al. have developed the COV19-CT-DB database for COVID-19, consisting of about 5,000 3-D CT scans [20], while Bohnstingl et. al. have revisited the incorporation of biologically-plausible models into deep learning [21].

3. Methodology

The methodology section of this study outlines the research design, data collection, and analysis techniques employed to address the research questions. This section aims to provide a clear and concise description of the methods used to ensure the validity and reliability of the study's findings. This section will also discuss any potential limitations or weaknesses in the methodology and how they were addressed. The methodology used in this study was carefully chosen to meet the research objectives and to ensure that other researchers could replicate the results.

3.1 Data Acquisition

The data used in this study was obtained from multiphase flow meter equipment installed at the offshore platform for well-testing activities. The flow meter equipment provided measurements of the flow rate of oil, gas flow rate, pressure, temperature, and oil density at one measurement per second. The data was collected for two hours, resulting in 36,000 data points per well. There are five wells for input data, resulting in 180,000 data points.

The data was divided into two states, before troubleshooting and after troubleshooting. The troubleshooting involved checking and repairing any malfunctioning components in the flow meter equipment. The data collected before troubleshooting was used as the baseline data, while the data collected after troubleshooting was used to evaluate the performance of the proposed deep learning-based abnormality detection model. The data was also screened for outliers and missing values. Any outliers or missing values were removed or imputed using appropriate techniques.

3.2 Recurrent Neural Network (RNN)

This study proposed a deep learning approach for detecting abnormality in multiphase flow meter data. Specifically, a type of deep learning called recurrent neural network (RNN) is well-suited for sequential data analysis using Python. RNN can capture the temporal dependencies of time-series data and has shown great success in various applications, including natural language processing, speech recognition, and image classification.

At first, the data was pre-processed by converting it into a time-series format to apply RNN to the multiphase flow meter data. The RNN model was built using Keras, a popular deep learning library, and trained using pre-processed data. The model consisted of multiple layers of LSTM (Long Short-Term Memory) cells, a type of RNN cell that can learn long-term dependencies in time-series data [22].

The RNN model was trained on the data in the so-called “before troubleshooting” state, and the trained model was then used to detect abnormality in the data from the “after troubleshooting” state. During abnormality detection, the RNN model could predict the expected output values based on the input values and the learned patterns in the data. Any significant deviation from the predicted values was considered abnormal, triggering an alert. Overall, using deep learning RNN in this study allowed for accurate and efficient abnormality detection in the multiphase flow meter data.

3.3 Evaluation Metrics

Accuracy is a commonly used metric to measure the performance of a model. It is calculated as the ratio of correct predictions to the total number of predictions made by the model. While accuracy is a good measure of overall performance, it can sometimes be misleading, mainly when the classes are imbalanced. For example, if a model has 95% accuracy, but the data is heavily skewed towards one class, the model may be simply predicting the majority class all the time. Therefore, it is important to consider other evaluation metrics besides accuracy. It is calculated as below.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{1}$$

Where TP is the number of true positives (correct positive predictions), TN is the number of true negatives (correct negative predictions), FP is the number of false positives (incorrect positive predictions), and FN is the number of false negatives (incorrect negative predictions).

F1-score is a metric that combines precision and recall. Precision is the ratio of true positive predictions to the total number of positive predictions, while recall is the ratio of true positive predictions to the total number of actual positives in the data. F1-score is calculated as the harmonic mean of precision and recall and is particularly useful when the classes are imbalanced. It ranges between 0 and 1, with higher values indicating better performance. It is calculated as below.

$$F1 - score = \frac{2TP}{(2TP+FP+FN)} \tag{2}$$

Where TP is the number of true positives (correct positive predictions), FP is the number of false positives (incorrect positive predictions), and FN is the number of false negatives (incorrect negative predictions).

Recall is a metric that measures the ability of a model to identify all relevant instances of a class in the data. It is calculated as the ratio of true positive predictions to the total number of actual positives in the data. A recall is particularly important in applications where missing a positive instance can have severe consequences, such as in medical diagnosis. It is calculated as below.

$$Recall = \frac{TP}{(TP+FN)} \tag{3}$$

TP is the number of true positives (correct positive predictions), and FN is the number of false negatives (incorrect negative predictions).

The receiver operating characteristic (ROC) curve is a plot that shows the trade-off between the true positive rate (sensitivity) and false positive rate (1 - specificity) of a model across different decision thresholds. AUC (Area Under the Curve) is a commonly used metric to summarize the ROC curve, with higher values indicating better performance. ROC curve and AUC are particularly useful when the model operates at different decision thresholds or when the classes are imbalanced.

Model accuracy and model loss are metrics used during the training process to assess the model’s performance on the training and validation data. Model accuracy is calculated as the ratio of correct predictions to the total number of predictions made by the model during training. Model loss is the value of the loss function used to optimize the model during training. Training a deep learning model aims to minimize the model loss and maximize the model accuracy on the validation data while avoiding overfitting the training data.

In summary, when evaluating a deep learning model, it is important to consider multiple evaluation metrics, including accuracy, F1-score, recall, ROC curve, AUC, model accuracy, and model loss. Each

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metric provides a different perspective on the model's performance and can help identify potential areas of improvement. A complete picture of the deep learning model's performance and areas for improvement may be seen by considering various evaluation criteria.

4. Results and Discussion

In this section, the results of our research will be presented, and a comprehensive analysis of the data collected will be provided. First, the descriptive statistics were presented, and then the study's main findings and implications were discussed. Finally, the limitations of our study will be discussed, and recommendations for future research will be provided.

The data from well-testing results were identified as input features. The input features were loaded from an Excel file using Panda's library and then pre-processed using Principal Component Analysis (PCA) for dimensionality reduction. The target labels were also pre-processed using label encoding and one-hot encoding. The RNN model was defined using the Keras library, with a SimpleRNN layer followed by two dropout layers and two dense layers. The model was then compiled using categorical cross-entropy as the loss function and the Adam optimizer. Early stopping was used to prevent the overfitting of the model.

The model was trained on the training data using a batch size of 32 and a validation split of 0.2. The training process was saved in the 'history' variable. The accuracy, F1 score, and recall were calculated using sci-kit-learn metrics and printed to the console. The model was then used to predict the well types on the test set, and the predicted classes were compared to the actual classes using the sci-kit-learn metrics. A receiver operating characteristic (ROC) curve was generated using the predicted probabilities, and the area under the curve (AUC) was calculated.

Table 1 - Summary of input features used in the RNN model for well-classification

Parameter	Value / Type
RNN input shape	(n_samples, 5, 1)
RNN hidden layer size	16
Dropout rate for RNN	0.5
Number of dense layers	2
Dense layer sizes	32, 5
Dropout rates for dense layers	0.6
Loss function	categorical crossentropy
Optimizer	adam
Early stopping	monitor='val_loss', patience=5

Finally, the model loss and accuracy were plotted over epochs using Matplotlib, providing visual feedback on the model's performance during training. Table 1 shows the parameters used as input features in the RNN model for well classification.

After troubleshooting the issues of the instruments part of the multiphase flow meter, we significantly improved our results. Our new model now has an accuracy of 99.48%, correctly classifying 99.48% of the total instances in the dataset, as shown in Fig. 2. This is a substantial improvement over the previous model's accuracy of 88.58%, as shown in Fig. 1.

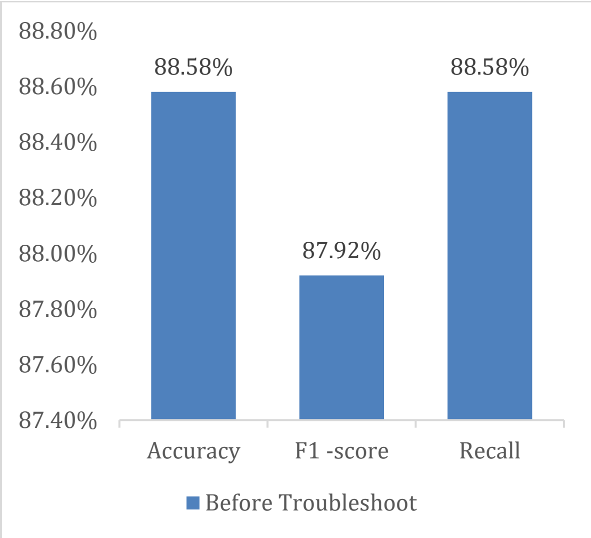

Fig. 1 - Evaluation metrics before troubleshooting the multiphase flow meter

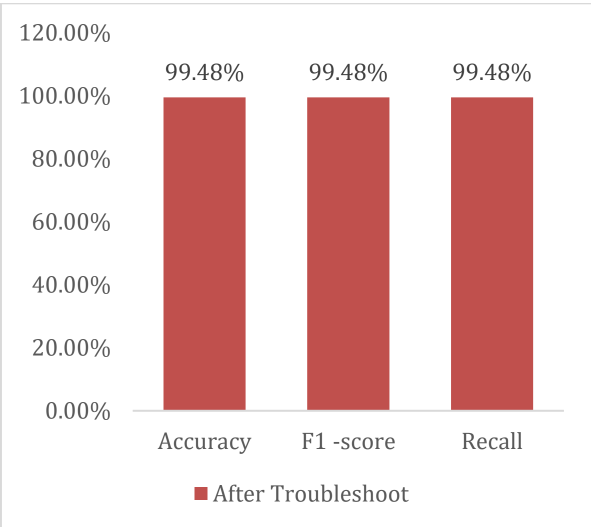

Fig. 2 - Evaluation metrics after troubleshooting the multiphase flow meter

In addition to accuracy and F1-score, we also evaluated our model's recall, which is the percentage of true positive cases that our model correctly identifies. Our new model achieved a recall of 99.48%, significantly improving over the previous model's recall of 88.58%.

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Our new model's results significantly improve accuracy, F1-score, and recall. These improvements can be attributed to our careful troubleshooting process, which allowed us to identify and address the issues impacting our model's performance. With these results, we can be confident in the effectiveness of our model for classifying instances in our dataset.

A Receiver Operating Characteristic (ROC) curve is a plot that illustrates the performance of a classification model at various classification thresholds. It is a way to evaluate the performance of a classifier by calculating the True Positive Rate (TPR) and False Positive Rate (FPR) at different thresholds. The TPR is also known as sensitivity or recall, and FPR is the ratio of negative instances that are incorrectly classified as positive.

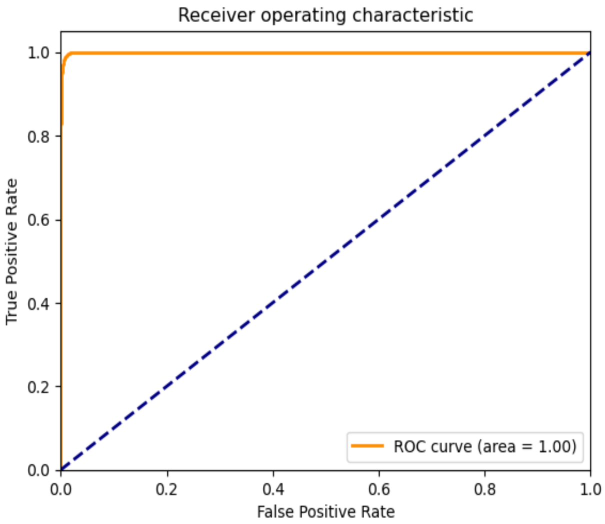

Fig. 3 - ROC curve of the RNN model

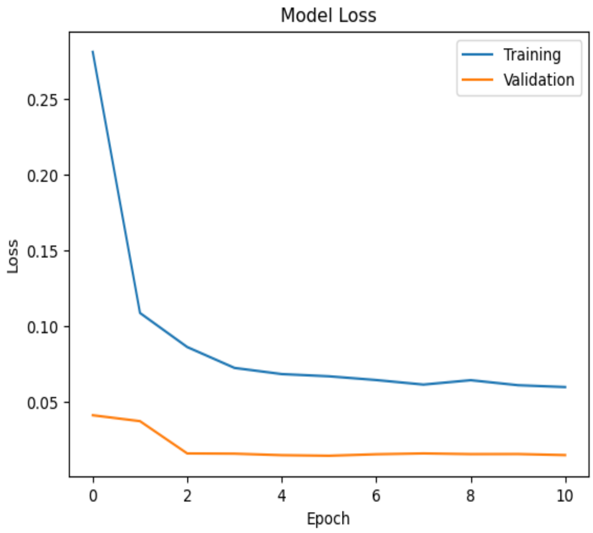

Fig. 4 - Performance of model loss graph of the RNN model

In this case, we obtained an ROC score of 1.00 after troubleshooting the multiphase flow meter, which is the highest possible score, indicating that the model has perfect discrimination ability, as shown in Fig. 3. This means the model can distinguish between positive and negative instances without any false positives or negatives.

A perfect ROC curve means that the model correctly classifies all positive and negative instances as negative, without making any errors. In practice, achieving a perfect ROC score is very rare, but it is a desirable outcome to aim for classification tasks. Achieving an ROC score of 1.00 indicates that the model performs well and can be considered a reliable and accurate classifier for the task at hand.

In machine learning, the loss function is used to measure how well the model is performing. The model attempts to minimize the loss during training by adjusting its weights and biases. In our case, the model seems to have achieved a good fit, as evidenced by decreased loss throughout training and converging at epoch 10. This means the model makes accurate predictions and does not overfit the training data. Overall, the excellent fit of the loss graph, as shown in Fig. 4, indicates the model's effectiveness in accurately classifying the data.

This study evaluated the model's accuracy using the training and validation datasets, as shown in Fig. 5. The accuracy is defined as the percentage of correctly classified data. The model was trained for ten epochs, and the accuracy improved steadily throughout the training process. The validation accuracy plateaued at epoch 10, indicating that the model had converged and further training would not result in significant improvements in accuracy.

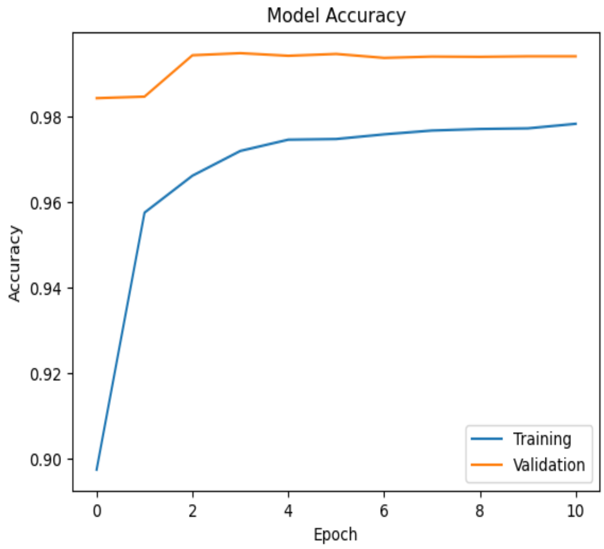

Fig. 5 - Performance of model accuracy graph of the RNN model

The accuracy graph showed a good fit, with the training and validation curves following a similar trajectory and converging at high accuracy. This indicates that the model is not overfitting or underfitting the data and can generalize well to new data. These results demonstrate the effectiveness of the model and its potential for real-world applications.

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While the proposed deep learning-based abnormality detection method using RNN demonstrated impressive accuracy in identifying abnormalities in the multiphase flow meter, some limitations should be considered. Using historical data to train and test the RNN model may not fully capture the current conditions or variations in the meter's behaviour over time. Future studies could collect real-time data to improve the model's accuracy. The study did not compare the RNN model's performance to other abnormality detection methods or discuss the potential costs of implementing and maintaining the method in practice. Future research could investigate the impact of different parameters and features on the RNN model's accuracy and explore developing a predictive maintenance system to further improve the method's performance. Finally, a cost-benefit analysis of implementing the abnormality detection method could help determine if the potential benefits of reduced downtime and maintenance costs outweigh the initial investment and ongoing maintenance expenses.

5. **Conclusion**

Based on the results of this study, it can be concluded that the proposed RNN model has shown promising performance in detecting abnormalities in multiphase flow meter monitoring. The model achieved an accuracy of 88.58% before troubleshooting, which was further improved to 99.48% after troubleshooting. These results suggest that the RNN model can effectively identify initial problems in the multiphase flow meter and guide necessary repairs. Furthermore, after the repairs, the RNN model was used to validate the performance of the multiphase flow meter. The high accuracy, F1-score, and recall of 99.48% demonstrate the model's ability to validate the multiphase flow meter's functioning after repairs accurately. Therefore, the proposed RNN model can be a reliable tool for monitoring and maintaining multiphase flow meters, improving overall performance and reducing downtime.

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