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AI-Driven Payroll Anomaly Detection In Oracle Cloud Payroll System

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Abstract- — This research study examines incorporation of an AI based anomaly detection method of Oracle cloud Payroll to make the payroll more accurate, reduce risks, and enhance compliance. The performance of different machine learning models such as Isolation Forest, One-Class SVM, Neural Networks, and Logistic Regression is tested in terms of their performance in detecting payroll data anomalies. Findings indicate that models such as Logistic Regression performed moderately well but other models did not cope with false positives and poor anomaly detection. The future is to perfect the models, involve deep learning, and realize the real-time anomaly to make the payroll management in large organizations more efficient and accurate.

Keywords: AI based anomaly detector, Oracle Cloud Payroll, payroll accuracy, machine learning models, Isolation Forest, One-Class SVM, Neural Networks, Logistic Regression, fraud detection, compliance, real-time detection, payroll anomalies

I. INTRODUCTION

Payroll management is one of the most important phenomena of Human Capital Management (HCM) systems, where there are large amounts of transactions to be processed, such as compensation, benefits, and calculation of taxes. Although platforms such as Oracle Cloud Payroll have been automated, mistakes, fraud, and compliance challenges remain, as the rules are complex, and their overrides are done manually. Conventional validation solutions are proactive and can take time and cannot detect anomalies real-time.

Research aim

This study aims to explore the Artificial Intelligence methods that can be integrated into Oracle Cloud Payroll to increase the detection of payroll anomalies, minimize financial risks, and improve compliance accuracy with predictive analytics.

Research Objectives

- To determine the effectiveness of AI-based anomaly detection in payroll systems.
- To determine key AI techniques that can be incorporated in Oracle Cloud Payroll.
- To determine the effectiveness of AI-based solutions in terms of payroll accuracy and regulatory compliance.

Problem Statement

Existing payroll systems are based on the predefined rules and manual audits, which do not recognize any abnormal payment patterns or fraud in large data sets. The organizations do not have living smart systems that detect anomalies before execution of payroll. This study discusses the implementation of Artificial Intelligence methods to Oracle Cloud Payroll to identify anomalies, minimize risks, and enhance compliance accuracy with the help of predictive analytics.

Novel Contribution

This research introduces a novel approach by integrating Artificial Intelligence with Oracle Cloud Payroll to identify anomalies in real time. It improves the accuracy and compliance of payrolls by predicting abnormalities in payment patterns and fraud in advance through predictive analytics. The research helps in coming up with smart payroll systems that are adaptable to data learning, thus enhancing risk management and operational efficiency in the payroll processing.

II. LITERATURE REVIEW

Effectiveness of AI-driven Anomaly Detection in Payroll Systems

Fig. 1: AI-driven Anomaly Detection in Payroll Systems

Payroll systems have evolved with automation, however, the errors like fraud and miscalculations remain, and the main reasons are the predetermined rules and manual audits [1]. The conventional systems are not able to identify minute abnormalities in payroll information thus presenting a potential risk [2]. An AI-based anomaly detection can be a remedy because it uses machine learning algorithms to process large datasets in real-time to detect latent inconsistencies [3]. These systems are self-learning and adaptive and monitor unusual payroll activity, thereby nipping problems in the bud before they get out of control. AI methods, especially unsupervised learning, can be fruitful in the detection of anomalies [4].

The methods are able to determine unforeseen deviations in payroll even without any prior information on normal behavior [5]. Through the historical payroll data, AI systems can establish a baseline and identify anomalies not in line with historical data [6]. This not only does this transition to proactive instead of reactive anomaly detection save on manual labor but lowers the risks of payroll errors and fraud as well [7]. The accuracy of AI systems can be constantly optimized, such as deep learning models, which detects the issue and becomes better with time, preventing the appearance of a problem that may affect the organization or its staff.

Key AI Techniques for Integration into Oracle Cloud Payroll

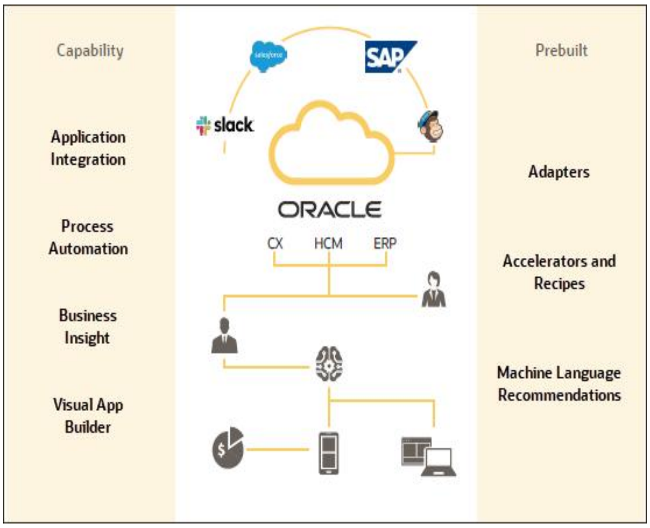

Fig. 2: Integration of Oracle Cloud Payroll

Integrating AI into Oracle Cloud Payroll can help to refine anomaly detection and streamline payroll operations [8]. A variety of machine learning methods can be used for this integration [9]. The discrepancies, fraud detection and optimization of payroll forecasting can be predicted using supervised learning models which are models that require labeled datasets to learn how to predict the result [10]. These models have the ability to be trained to learn patterns in the payroll transactions and forecast anomalies in the future based on historical behavior [11].

The unsupervised learning techniques also play an important role in detecting anomalies [12]. These models lack the need of labeled data and are best suited to detecting suspicious payroll trends with no predetermined rules [13]. The algorithms are especially useful with large organizations that require large volumes of payroll data processed, which, using manual rule-based methods, would be inefficient and subject to error [14].

Another significant AI method in the payroll system is Natural Language Processing (NLP), particularly in unstructured information like the communication of employees and audit trails [15]. NLP is able to derive meaningful information out of text data, which assists in detecting possible problems with payroll discrepancies or fraud [16].

These AI methods can be effectively incorporated into Oracle Cloud Payroll to increase the payroll processing, elevate the accuracy, and compliance [17]. Through these approaches, organizations are able to develop a more effective, smarter payroll system that is able to cope with new challenges and changing regulatory landscapes.

Impact of AI-based Solutions on Payroll Accuracy and Regulatory Compliance

Fig. 3: Payroll Compliance

AI-driven solutions are also providing major improvements in the accuracy of the payroll and compliance with regulations [18]. The old systems of payroll have a tendency to be both static systems and rule systems and therefore cannot keep up with the fluctuating regulations and complicated calculations [19]. AI leads to better payroll processing through overtime, benefits, tax reduction, and bonuses calculation automation [20]. The consistency of AI models increases with time as it gets to learn previous payrolls and minimize the probability of errors and inconsistencies [21].

Besides enhancing accuracy, AI solutions can be uniquely practical in terms of regulatory compliance [22]. Payroll systems are required to comply with a broad spectrum of taxation, labor and benefits legislation that differs with jurisdiction [23]. The AI-powered payroll processing system can be automatically updated with the latest regulation, that the processes of paying the employees are never in violation of the local and national laws [24].

The fact that AI can keep track of regulatory changes in real time and update payroll computation accordingly minimizes a risk of expensive fines and penalties imposed in case of non-compliance [25]. The capabilities of AI when it comes to the real-time detection and resolution of any anomalies enable detection of issues swiftly and can ensure that it does not reach employees or regulators.

Use of AI in payroll systems is especially useful to organizations with many employees and a complicated payroll system since AI is able to process large volumes of data with ease [26]. Automating complicated payroll processes can not only minimize the chance of a human error but also properly and punctually remunerate the employees.

III. METHODOLOGY

Research Design

This study is based on quantitative research design as it attempts to examine the implementation of AI-based anomaly detection on Oracle Cloud Payroll systems. The goal is to evaluate the possibilities of AI methods to identify payroll abnormalities, reduce risks, and increase compliance [27]. Important models, such as Isolation Forests, One-Class SVM, and logistic regression are used to detect payroll dislocation, fraud and compliant breaches prior to payroll disbursement.

Data Collection

The data used in this study is derived using a simulated Oracle Cloud Payroll system which offers payroll information including payroll transactions like compensation, overtime, benefit deductions, tax calculations and compliance information. The data is anonymized in the form of normal payroll data and historical abnormalities such as unauthorized rate adjustments or duplicates. It divides data into training and test groups to train and test AI models.

Data Analysis Plan

The data analysis plan focuses on the following steps:

Preprocessing: Cleansing of data is performed to eliminate missing and outliers. It performs feature engineering to obtain the information as hours of overtime, pay rate and tax code.

Exploratory Data Analysis (EDA): Simple descriptive statistics, distributions, and correlations among the components of payroll will be discussed. This facilitates finding any notable trends or patterns in the data.

Model Development and Training: Oracle Machine Learning (OML) embedded in the Oracle Autonomous Database is used to create the AI models. For identifying payroll differences, both supervised and unsupervised learning models are used.

AI Model Development

For identification of the payroll anomalies, the machine learning models below are utilized:

Isolation Forests: This model is effective in identifying anomalies, including duplicate payments or a sudden increase in hours worked by isolating the outliers in data. It is employed to detect odd transactions in payroll [28]. The anomaly score A(xi) of a data point xi at point xi is obtained as:

$$A\,(xi)\ = 2^{-\frac{h\,(xi)}{c(n)}}$$

Where:

h(xi) is the number of splits needed to isolate data point xi.

c(n) is the path length of n data points on the tree on average.

One-Class Support Vector Machines (SVM): The One-Class SVM is a valuable unsupervised anomaly detector that is used to analyze large volumes of data consisting of normal payroll records in order to identify major anomalies that might signal fraud or inaccuracies. The optimization problem is defined as:

$$min_{w,b,v}\frac{1}{2}\parallel w\parallel^2 + C\sum_{i=1}^{N}\quad \xi i$$

Where:

w is the weight vector.

b is the bias term.

ξi are slack variables.

The width of the margin is determined by C.

N is the number of data points.

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Neural Networks: A sophisticated model of the neural network able to learn complex patterns in payroll data and provoke a more complex scheme of fraud that simpler models cannot identify. Such models assist in detecting complicated anomalies in payroll information. These models identify the complicated patterns of payrolls based on loss object, and the loss object is:

$$min_{w,b,v}\frac{1}{2}\| w \|^2 + C\sum_{i=1}^{N} \quad \xi i$$

Where:
yi is the true value.
$\widehat{y}_i$ is the predicted value.
N is the number of data points.

Logistic Regression: A supervised model that requires labeled past data, logistic regression classifies payroll records as normal or anomalous, per defined criteria. It is useful especially in establishing the known payroll problems using past datasets.

$$P(y=1|x) = \frac{1}{1+e^{-(W^T X + b)}}$$

Where:
P(y=1 | x) is the probability that x is anomalous.
w is the weight.
x is the input feature vector.
b is the bias term.
e is Euler's number.

Model Evaluation

The AI model is assessed in terms of accuracy, precision, recall and F1-score and Area Under the Curve (AUC). The confusion matrix is used to assess classification performance:

TP corresponds to true positive; TN corresponds to true negative; FP corresponds to false positive and FN corresponds to false negative. Cross-validation helps to guarantee strength since the data is divided into several samples and the model is applied and tested on new areas.

Visualization Charts

The findings of AI models are visualized, that the payroll administrators can monitor the abnormalities in real time. The essential visualizations are heat maps, which indicate compliance risks, and indicate regions with late submission or misclassification of the tax. Scatter plots with meshgrids plots payroll characteristics such as base pay against the overtime and detect outliers. The trends of payroll are monitored using time-series line charts, and the payroll anomalies are indicated by AI confidence bands. SHAP value plots clarify the model choices, whereby, what factors raise anomaly flags.

Architecture Diagram

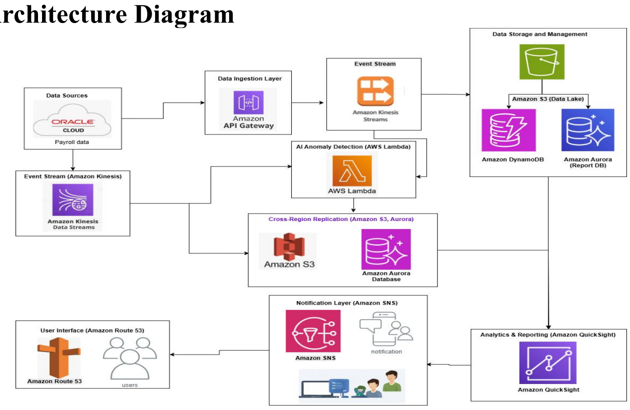


Fig. 4: Architecture Diagram

The architecture diagram defines the pay-roll anomaly detection system that is operated with the help of AI. It combines Oracle Cloud to access payroll data, Amazon Kinesis to stream events and has a combination of AWS Lambda to identify anomalies and Amazon QuickSight to analyze data.

Flowchart

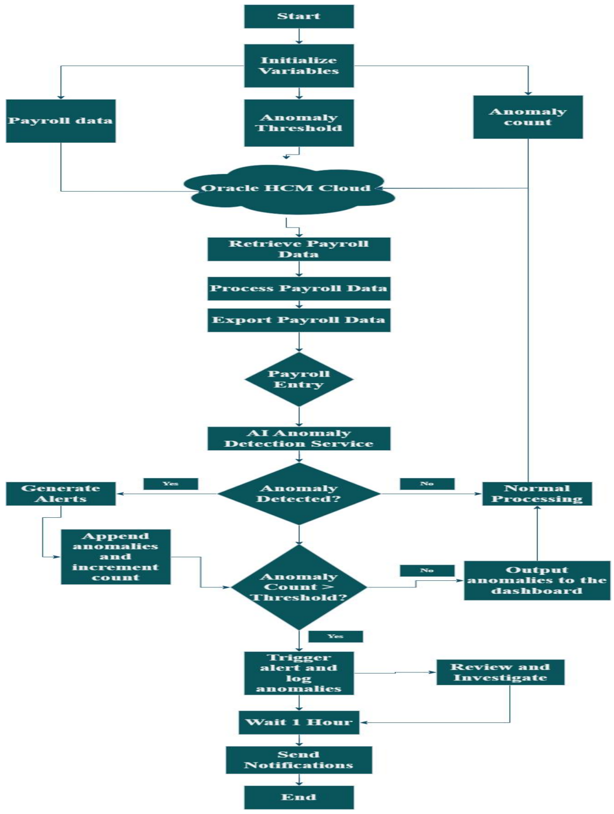


Fig. 5: Flowchart

The flowchart describes the steps to be followed when identifying anomalies in the payroll subjects in the Oracle HCM Cloud with the help of AI. It involves data retrieval, detection of anomaly, generation of alerts, logging and sending of notification, that can make it more compliant and reduce the risk.

Pseudocode

```
Program start
  Initialize variable payroll_data
  Initialize variable anomaly_threshold
  Initialize variable anomaly_count = 0
  Initialize variable detected_anomalies = []

  Connect to Oracle HCM Cloud (Payroll System)
  Retrieve latest payroll data from Oracle HCM Cloud

  Start infinite loop
    Process the latest payroll data
    For each payroll entry in payroll_data:
      Call function DetectAnomaly with input payroll_entry
      If DetectAnomaly returns True:
        Append payroll_entry to detected_anomalies
        Increment anomaly_count

    Output detected_anomalies to HR Admin dashboard
    If anomaly_count > anomaly_threshold:
      Trigger alert to HR Admin
      Call function LogAnomaly to store anomalies in database

    Call function Delay for 1 hour to check for new payroll data
  End infinite loop

Program end
```

Fig. 6: Pseudocode

This pseudo-code describes an AI-based payroll anomaly detection system that connects to the Oracle HCM Cloud to retrieve the payroll information, processes the information, sends notifications to HR administrators and documents the identified anomalies to ensure compliance.

J.Impact Assessment

The effect of AI on payroll accuracy and compliance with labor laws is measured in terms of the performance of the AI model over the two conventional systems. AI's effectiveness in ensuring compliance with regulations, such as tax laws and benefits, are assessed by monitoring the impact of the model, detecting regulatory discrepancies.

K.Ethical Considerations

Anonymization of data is essential to maintain data privacy. Aggregated payroll information is utilized to make sure that privacy laws are adhered to. Moreover, AI models are programmed to provide fairness and transparency such that it is interpretable and provide accountability in decision-making.

L.Real-Time Implementation

The AI models are incorporated into a simulated Oracle Cloud Payroll system, whereby it assesses payroll transactions in real time. The effectiveness of the AI solution shows the decrease of payroll errors and anomalies found prior to implementation (traditional methods). Such adoption shows AI scalability and its effectiveness in big organizations.

IV. RESULT AND DISCUSSION

```python
# Data Preprocessing - Handling Missing Values and Outliers
def preprocess_data(df):
    df.fillna(df.mean(), inplace=True)  # Filling missing values
    df = df[(df['hours_worked'] < df['hours_worked'].quantile(0.95)) & (df['hours_worked'] > df['hours_worked'].quantile(0.05))]  # Remove outliers
    return df
```

Fig. 7: Data Preprocessing

The code shows the data preprocessing for the payroll analysis where the data in the hours worked column that contains missing values are replaced with the mean, and all the outliers (above the 95th percentile and below the 5th percentile) are eliminated to have clean, reliable data to detect anomalies in payroll processing.

```
Descriptive Statistics:

              payroll_date  hours_worked     base_pay    overtime  \
count                  100    100.000000   100.000000  100.000000
mean   2022-02-19 12:00:00    159.396196  2984.725234   99.230226
min    2022-01-01 00:00:00    134.844202  2346.343774   62.531948
25%    2022-01-25 18:00:00    151.321434  2879.492615   83.246907
50%    2022-02-19 12:00:00    159.990027  2986.910866   99.140650
75%    2022-03-16 06:00:00    167.243882  3125.030717  113.041826
max    2022-04-10 00:00:00    182.474524  3419.252947  154.680902
std                    NaN     10.667066   200.325850   22.036653

       is_anomalous
count    100.000000
mean       0.530000
min        0.000000
25%        0.000000
50%        1.000000
75%        1.000000
max        1.000000
std        0.501614
```

Fig. 8: Descriptive statistics

The descriptive statistics give insights of payroll data where average hours worked (159.40); base pay (2984.73) and overtime (99.23) can be seen. The mean of the anomalous column is 0.53, which means that anomaly detection is balanced.

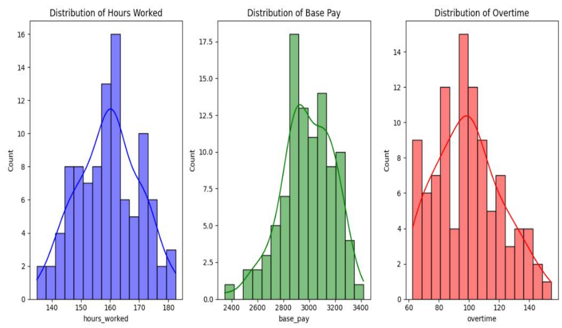


Fig. 9: Distribution of Payroll features

The histograms indicate the distribution of the most important payroll characteristics. The majority of employees worked 160 hours, and there are some exceptions. The minimum and maximum base pay range is between 2800 to 3200 and it is almost normal. There are 80 and up to 120 overtime hours, slightly skewed toward the higher amount. These distributions are significant to detect the anomalies and payroll abnormalities.

```
Isolation Forest - Accuracy: 0.5555555555555556, Precision: 0.2, Recall: 0.02702702702702703, F1: 0.047619047619047616
Confusion Matrix:
[[49  4]
 [36  1]]
```

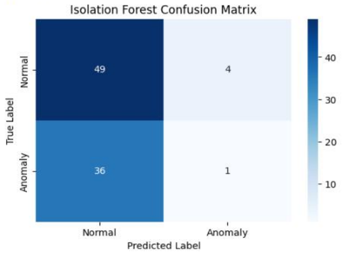


Fig. 10: Isolation Forest model Evaluation

The Isolation Forest model analyses the payroll data, which produces an accuracy of 55.56, precision of 0.2 with a recall of 0.027. The confusion matrix indicates that there are 49 cases of true positives (normal) and 36 cases of false positives (anomalies predicted as normal). There is only 1 correct identification of an anomaly, which indicates that this model is not very effective in differentiating between anomalies and normal transactions.

```
One-Class SVM - Accuracy: 0.3888888888888889, Precision: 0.375, Recall: 0.7297297297297297, F1: 0.4954128440366973
Confusion Matrix:
[[ 8 45]
 [10 27]]
```

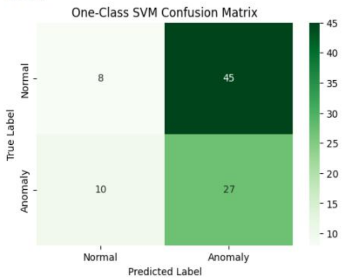


Fig. 11: One-Class SVM Evaluation

One-Class SVM model has an accuracy of 38.89, precision of 0.375 and a recall of 0.73. The confusion table shows the existence of 8 true positives(normal), 45 false positives (anomalies predicted to be normal), and 10 false negatives (normal predicted anomalies). This implies that the model has a high false positive rate, meaning that it is not very effective in correctly identifying normal payroll records.

```
# Neural Network Model for Anomaly Detection
def neural_network(df):
    model = MLPClassifier(hidden_layer_sizes=(100, 50), max_iter=500)
    X = df[['hours_worked', 'base_pay', 'overtime']]
    y = df['is_anomalous']
    model.fit(X, y)
    df['anomaly_nn'] = model.predict(X)
    return df
```

```
Neural Network - Accuracy: 0.5888888888888889, Precision: 0.0, Recall: 0.0, F1: 0.0
Confusion Matrix:
[[53  0]
 [37  0]]
```

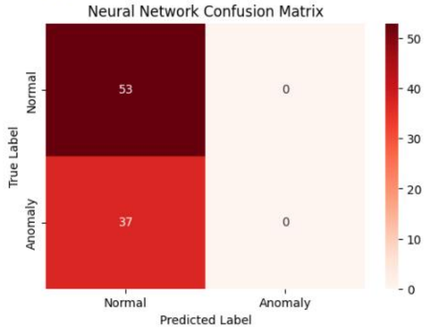
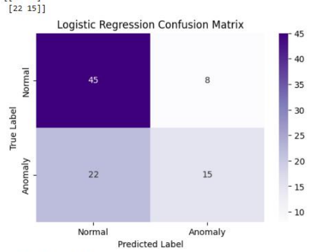


Fig. 12: Neural Network Evaluation

The Neural Network model attained the accuracy of 58.89 with the precision, recall and F1 score of 0. This implies that no anomalies are introduced to the model, and this is indicated in the confusion matrix. The model is able to identify all the 53 normal records correctly, and it cannot identify any anomalies with 37 false negatives. This is a pointer to the fact that the model has to be improved when it comes to detection of anomalies.

```
# Logistic Regression Model for Anomaly Detection
def logistic_regression(df):
    model = LogisticRegression()
    X = df[['hours_worked', 'base_pay', 'overtime']]
    y = df['is_anomalous']
    model.fit(X, y)
    df['anomaly_lr'] = model.predict(X)
    return df
```

```
Logistic Regression - Accuracy: 0.6666666666666666, Precision: 0.6521739130434783, Recall: 0.40540540540540543, F1: 0.5
Confusion Matrix:
[[45  8]
 [22 15]]
```




```
(0.6666666666666666,
 0.6521739130434783,
 0.40540540540540543,
 0.5,
 array([[45,  8],
        [22, 15]]))
```

Fig. 13: Logistic Regression Evaluation

The accuracy of the Logistic Regression model is 66.67, precision of 0.65, recall of 0.40 and F1-score of 0.5. The confusion matrix shows that 45 norms records and 15 anomalies have been correctly identified, 22 anomalies are predicted to be considered normal, and 8 norms are predicted to be anomalies are wrong. The model is moderate and needs additional refinements in detecting anomalies.

Table 1: Key Performance Metrics (Accuracy, Precision, Recall, F1 Score) For Different Models

Model	Accuracy	Precision	Recall	F1 Score	True Positives (Normal)	False Positives (Anomalies Predicted as Normal)	False Negatives (Normal Predicted as Anomalies)	True Negatives (Anomalies)
Isolation Forest	55.56 %	0.20	0.027	0.048	49	36	0	4
One-Class SVM	38.89 %	0.375	0.73	0.495	8	45	10	27
Neural Network	58.89 %	0.00	0.00	0.00	53	0	37	0
Logistic Regression	66.67 %	0.65	0.40	0.50	45	8	22	15

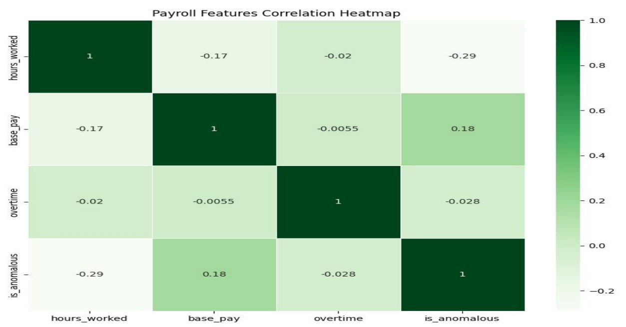


Fig. 14: Payroll Features Correlation Heatmap

The heatmap of correlation depicts weak correlations between payroll features. The greatest correlation is between base pay and is anomalous (0.18) and the minimum is between hours worked and is anomalous (-0.29). These findings have indicated minimal correlations between payroll aspects and anomalies indicating the necessity of more sophisticated methods of detecting anomalies.

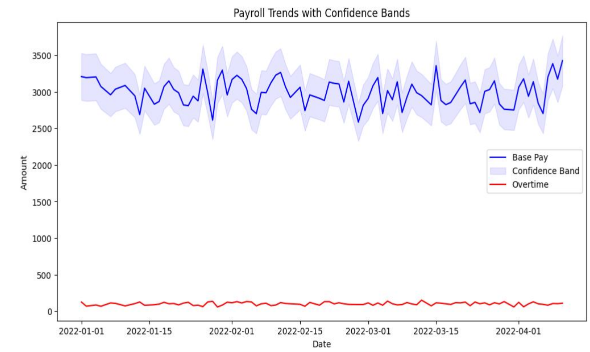


Fig. 15: Payroll Trends with Confidence Bands

The time-series plot indicates that base pay varies between 2500 and 3500 with confidence bands illustrating what should be expected. Overtime is also a very fixed cost, below 500, indicating that there is not much change in the payments of overtime.

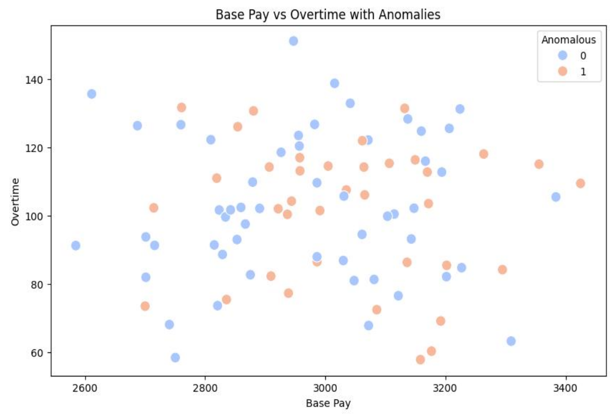


Fig. 16: Scatter Plot with Meshgrids - Payroll Characteristics

The scatter plot shows base pay and overtime, with blue points as indicating normal transactions and orange points as anomalies. The vast majority of the anomalies are found in the range of base pay of between 2800 and 3200 and overtime of between 90 and 130.

Discussion

The preprocessing stages of data ensure that no malicious payroll data is presented due to missing information and outliers. The descriptive statistics showed the mean time spent at work (159.4), salary (base pay) (2984.73), and the mean time spent in the overtime (99.23) with the is anomalous column showing a balanced mean (0.53) to show a reasonably fair distribution of anomalies. Analysis of the distribution revealed that the majority of the employees are working about 160 hours with the OT having a clustering of 80-120 hours whereas the base pay had a near-normal distribution.

Such insights play an important role in identifying irregularities in payroll transactions. In terms of model performance, Isolation Forest had an accuracy of 55.56, although it did not perform well on false positives, only 1 true anomaly was detected. On the same note, the One-Class SVM had a huge false positive rate and is associated with an accuracy of 38.89, which suggests the difficulty to determine normal and abnormal transactions.

The Neural Network model performed poorly with 0 precision and recall and is unable to hold onto the anomalies and Logistic Regression model performed averagely with 66.67% accuracy but with huge misclassifications. Correlation heatmap showed weak correlations especially between base pay and is anomalous (0.18). Through time-series charts, the base pay fluctuation is stable, and the scatter plot revealed model anomalies with 2800-3200 base pay and with overtime of 90-130, which needed an improvement of the models.

V. CONCLUSION

In conclusion, AI-based anomaly detection models have potential to detect payroll anomalies but need additional improvement. Although such models as Logistic Regression are average performers, advances in dealing with false positives, real-time identification, and integrating innovative methods are necessary to reach higher levels of accuracy and compliance in payroll.

Future Direction

The future research needs to enhance anomaly detection models by considering new methods, such as deep learning (Autoencoders), support of more complex payroll characteristics, and interpretability of the model. Also, the efficacy of payroll systems can be improved by adding real-time detecting anomalies and optimizing the balance between accuracy and recall recognizing the presence of irregularities more effectively and with the smallest number of false positives.

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