**COMPONENT 1**

**Abstract:**

The world is looking at renewable energy as an alternative to fossil energy. To achieve this, we need to look at the challenges, opportunities and success made in this field especially in false alarm reductions, fault detection, fault prevention and components repairs and cleanings.

The reviewed articles x-rayed how we can achieve these things using intelligent agents either individually or as a group.

The applications of Intelligent agents in the specific areas of renewable energy like FLOATING OFFSHORE WIND FARMs (FOWFs), solar energy and wind energy were covered to enable us to understand the progress made so far.

**Introduction:**

**(**Khalid et al., (2022) discussed Operation & Maintenance activities like inspections, maintenance, and repairs in floating offshore wind farms.

Teixeira et al. (2022) suggests a method for fault detection and condition monitoring in wind turbines applying model interactions and ANNs.

Deshmukha (2022) implemented a robot that is used for solar panel cleaning.

The last article reviewed global opportunities and challenges in the energy sector and how intelligent robots will play a role in resolving some of the challenges.

**Methodology:**

Detailed literature search was implemented on databases like UniHull library, ResearchGate, and Acedemia.edu, applying keywords related to intelligent agents in renewable energy. Four articles were selected, and data extraction, analysis, and were performed. Details are presented below:

**Applications of robotics in floating offshore wind farm operations and maintenance: Literature review and trends (Khalid et al., 2022)**

The **aim** of the reviewed article is to understand how intelligent robotics are used in operation and maintenance activities in floating offshore wind farms.

**One major contribution** is the development of **climbing robots and aerial robots**. This brought the **success** of using robots to carry out operations and maintenance(O&M) successfully in floating offshore wind farms (Khalid et al., 2022).

A close-up of a wind turbine

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Fig 1.0 – climbing robot (Khalid et al., 2022).

G**ap identified** is that Unlike the offshore assets, in-situ, and remote inspection of FOWFs is challenging hence it is difficult to do extensive verification, testing and validation of the O&M robotic systems in FOWFs (Khalid et al., 2022).

**Addressing this gap** will ensure extensive testing, validation, and inspection. This will ensure that the risk of deploying unintelligent robots that may not be ideal for FWOF is avoided.

**Applying Intelligent Multi-Agents to Reduce False Alarms in Wind Turbine Monitoring Systems** (**Teixeira et al., 2022).**

The **aim** is to propose a method for operational condition monitoring and fault detections that is based on behaviors using ANNs and model interactions from intelligent agents to improve monitoring performances thereby reducing false alarms in wind turbines.

Some of the **contributions** of Intelligent agents according to this article are:

* Establishment of methodology used to develop an industrial monitoring system.
* Application of information generated from several subsystems of industrial plants to improve fault monitoring and detection.
* Combination of MASs and behavioral models of normal behaviors generated using ANNs.
* Single indicator establishment for the operating conditions of all plant’s subsystems (Teixeira et al., 2022).

These contributions led to the **success of** the development of application of multi-intelligent agents that have the capability to reduce total number of false alarms by more than 20% in most critical systems of wind turbines.

**Gap** identified is that the data measurement time did not encompass stages of aging in wind turbines were significant anomalies like catastrophic failures and maintenance can affect the measurements and this may affect the proper evaluation of the developed model.

Failure to account for the stages of aging may cause the multi-agents developed not to capture accurately the changing behaviors of wind turbines over time.

**CLEAROSO: A Cleaning Robot for the Solar Panels** (**Deshmukha, 2022).**

The article aims to bring together technologies like DC motor, infrared, Arduino microprocessor, Bluetooth, application to develop a robot for the purpose of cleaning solar panels.

**One major contribution** is the development of robotic device that uses silicone rubber foam to clean PV modules efficiently (Deshmukha, 2022). **This led to the** **success** of the elimination of dust deposition that reduces the efficiency of the solar panels and eliminated human intervention in the solar panel cleaning thereby halving the cleaning time of solar panels.

A robot on a solar panel

Description automatically generated with low confidence

Fig 2.0 Robotic cleaning robots ([Dinneen](https://www.newscientist.com/author/james-dinneen/), 2023)

**Gap** observed is lack of provision of the efficiency and speed of automated robots at **an angular positioned solar panel.**

Addressing this gap will ensure **maximization of energy generation.** This is because speedy cleaning and efficient cleaning of solar panels positioned angularly is very important to retain maximum performance of solar panels.

**Artificial Intelligence in the Power Sector** (**Baloko Makala & Tonci Bakovic, 2020).**

The aim is to apply Intelligent agents to cut energy waste, theft, lower energy cost and improve the use of clean renewable energy globally.

S**uccess** identified is **Fault prediction and monitoring**: Intelligent agents have been effectively used to monitor and predict faults before they happen. This can be seen by the application of Maintenance facilitated by image processing by the UK National Grid using drones to monitor wires and pylons that transmit electricity from power stations to homes and businesses (Baloko Makala & Tonci Bakovic, 2020).

A helicopter flying over a city

Description automatically generated with low confidence

Fig 3.0 Robotic cleaning robots – application of drones by UK National Grid (Theron-Ord, 2017)

**One challenge** envisaged is lack of reliable connectivity especially where cellular network coverage is sparse or limited.

Addressing **this challenge** can unlock the adoption of renewable energy in emerging markets.

**Results:**

My results after reviewing the 4 articles showed two future opportunities that addressed two out of the 4 gaps identified. They are as follows:

1. **The development of intelligent robotic agents specifically made for remote inspection and in-situ in FOWFS.** Robotic agents should be equipped with advanced imaging devices, sensors, and manipulators designed for the specific challenges around the offshore environments.

This **contribution is important** as it will help to build a specialized robotics system that is well tailored to O&M activities in the FOWFs that has the capabilities to handles the issues of extensive testing, validation, and verification in unique environments like FOWFs.

1. **Advanced Navigation and Control Systems**. Intelligent robots(agents) that is equipped with advanced navigation and control features to navigate the complex solar panel surfaces placed at angle position, adjusting to various configurations and performs autonomous determination of optimal cleaning paths.

This **contribution is important** because it will lead to speed and efficiency in the cleaning of solar panels placed in angular positions.

**Conclusion:**

The reviewed articles showed the application of intelligent agents in the renewable energy sector, contributions, successes, challenges, and future opportunities. It shows that there is a need to research more and develop **intelligent agents specifically made for remote inspection and in-situ in FOWF** and **Advanced Navigation and Control Systems.**

**List of Reviewed Articles:**

* Applications of robotics in floating offshore wind farm operations and maintenance: Literature review and trends (Khalid et al., 2022)
* Applying Intelligent Multi-Agents to Reduce False Alarms in Wind Turbine Monitoring Systems (Teixeira et al., 2022).
* CLEAROSO: A Cleaning Robot for the Solar Panels (Deshmukha, 2022).
* Artificial Intelligence in the Power Sector (Baloko Makala & Tonci Bakovic, 2020).

**Reference**

Deshmukh, N.N., Chitale, D. and Kamath, R.C. (2022) CLEAROSO: A Cleaning Robot for the Solar Panels. *Journal of Computers, Mechanical and Management*, 1(2), 09-13.

Dinneen , J (2023) *Solar panel cleaning robot can be dropped off and picked up by drone*. New Scientist. Available online: <https://www.newscientist.com/article/2356066-solar-panel-cleaning-robot-can-be-dropped-off-and-picked-up-by-drone/> [Accessed 13 Apr. 2023].

Khalid, O., Hao, G., Desmond, C., Macdonald, H., McAuliffe, F.D., Dooly, G. and Hu, W. (2022) Applications of robotics in floating offshore wind farm operations and maintenance: Literature review and trends. *Wind Energy*.

Makala, B. and Bakovic, T. (2020) *Artificial Intelligence in the Power Sector*. www.ifc.org. Available online: <https://www.ifc.org/wps/wcm/connect/publications_ext_content/ifc_external_publication_site/publications_listing_page/artificial+intelligence+in+the+power+sector> [Accessed 24 Jun. 2021].

Teixeira, W.C.E., Sanz-Bobi, M.Á. and Oliveira, R.C.L. de (2022) Applying Intelligent Multi-Agents to Reduce False Alarms in Wind Turbine Monitoring Systems. *Energies*, 15(19), 7317.

Theron-Ord, A. (2017) *National Grid employs drones to monitor HV networks*. Smart Energy International. Available online: <https://www.smart-energy.com/regional-news/europe-uk/national-grid-drones-network/>.

**Title: Sales of Video Games**

**Abstract:**

The video game business is a quickly expanding market with many variables that might affect a game's success. This study uses a dataset of video games to investigate which characteristics or combinations of variables may most accurately forecast the global sales of video games. Additionally, the impact of user and critic numbers, as well as review scores on sales in the EU, Japan, and North America, is investigated. The dataset's categorical variables are also used to categorize the data and find the best-performing variable. The data are then grouped using a pertinent category variable, and the variable that best describes the groups is determined.

**Introduction:**The video game industry has expanded to be worth many billions of dollars, making it a successful enterprise. Therefore, it's crucial to comprehend the variables that affect video game sales. This research seeks to classify the dataset using pertinent category variables, evaluate the best categorical variable that describes the groups formed, and investigate the characteristics in the video game dataset that best predict global sales and their consequences.

**Methodology:** Python is used to acquire and analyze the video game dataset along with the Pandas, Matplotlib, Seaborn, and Scikit-learn modules. The preprocessing of the data includes handling missing values, eliminating superfluous columns, and encoding category variables. A correlation matrix is utilized to determine which variables have the strongest link with sales, and linear regression tree based regressors were used to forecast worldwide sales based on a variety of predictor variables. Using correlation matrices and scatter graphs, the effect of review ratings and the quantity of users and critics on sales in North America, the EU, and Japan were examined. The classification of the data based on categorical factors is performed using the decision tree, random forest, and K-Nearest Neighbor algorithms. The data are then grouped using K-means clustering based on a pertinent categorical variable, and internal and external evaluation to decide the best predictors.

**Results:** To get the full details of this analysis, the full details are provided as questions and answers. This is to enable us to understand in detail the best predictors and movers of different features that contribute to video games. Find below the full details starting with the first question.

1. **Which of the variables in the video game dataset or a combination of them best predicts “global sales” of video games and why? Provide quantitative justifications for your answers.**

The combination of the variables that best predicts sales in the target variable ‘Global Sales’ of video games in their other of their importance are NA Sales, Other Sales, JP Sales, and EU Sales. We have other contributors, but their contributions cannot be classified with the term ‘best predictions’ hence the reason for my choosing these four. The quantitative reason is as shown and explained below: (Please note that GradientBossting Regressor was used to build the model and retrieve the information provided below.

Worthy to note in this report is that the **PLATFORM** feature or variable was replaced or used interchangeably with the world **PLATFORMPRIMARY.** This is because of the method I applied in my data cleaning.

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The NA Sales accounts for the highest contribution with 0.5636. This showed that it is top among the independent variables that can be used to predict Global sales of Video games. What this means is that for every 1 unit of increase in North America (NA Sales), the Global Sales are expected to increase by 0.5636.

Coming to Other Sales, it accounts for 0.1810 contributions to the Global Sales of the video game. For every 1 unit of increase in Other Sales, Global Sales are expected to increase by 0.1810.

For JP Sales, it accounts for 0. 0.1477 contributions to the Global Sales of the video game. For every 1 unit of increase in Other Sales, Global Sales are expected to increase by 0.1477.

On the other hand, for every 1 unit of EU Sales, the Global Sales of video game is expected to increase by 0.1040.

Other variables like Critic Score, Critic Count, User Score, and User count showed that they don’t have enough contributions towards the Global Sales as their important features are reported to be less than 0.0001.

Apart from platforms of the games, other variables listed do not contribute enough to be termed best predicting variable.

The platforms for the game showed higher feature importance than the Ratings and Genres. This showed that they make some contributions to the target variable (Global Sales). However, these contributions are not significant enough when compared with the sales variable (NA\_Sales, Other\_Sales, JP\_Sales and EU\_Sales).

In summary, the combination of the variables, NA Sales, Other Sales, JP Sales, and EU Sales best predicts sales in the target variable (Global Sales of Video game).

1. **What effect will the number of critics and users as well as their review scores have on the sales of Video games in North America, EU, and Japan?**

**For North America:**

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The critical count has a feature of 0.2310 to sales in North America, while Critical score is 0.3447 which is an indication that Critical score has a stronger effect when compared with Critical count. The User count with feature importance of 0.4242 indicates the strongest effect on sales in North America when compared with all the featured features. The User has no effect on the sales in North America.

This implies that with every increase of unit of Critic Score, we have 34.47% sales increase in North America. For Critic Count, there is a 23.10% percent increase in sales in North America for every one-unit increase. The User Count increased the sales in North America by 42.42% for every one-unit increase. However, it is important to note that the relationships between sales in North America and the features are not casual and there is a possibility that othercontributed to influencing the sales.

**For EU:**

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The Critic Count here has the second highest effect with a score of 0.1321. The highest importance is User Count with the score 0.7581. The implication is that the number of critics and users that reviewed the game accounts for greater effect on the EU sales than their review scores (i.e., Critic score). However, the Critic score is still having an effect in the EU sales ah it has importance of 0.1099 which is still high. The implication is that higher review score provided by the critics has the potential to affect sales in the EU positively. The user score contributes nothing indicating that its effect on the EU sales is insignificant.

Overall, the feature of an important score is a pointer that the number of users and critics that reviewed the video games possess greater effect on the Sales in EU.

**For JP:**

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From the feature of importance values, it is clear to see that the number of critics and score reviewed possess a higher effect on the video sales in Japan when put in comparation with user score. The result showed that for every one unit in increase in Critic count, there is an expectation of increase of 0.261 (26.1%) units in sales in Japan. For critical score, there is 0.2744 (26.44%) increase in the video game sales in Japan for every unit increase in critical score. On the other hand, User count contributes highest with a value of 0.4645 and that means that for every one unit increase in User count, there is 46.45% effect in the sales of video games in Japan. The lowest feature of importance is User score with no impact on the sales of Video games in Japan.

1. **What propelled the choice of your regressor for this task? Aptly discuss with quantitative reasons!**

I chose Gradient Boosting as my regressor because of its performance. Before I chose this regressor, I built my model with 5 different regressors and evaluated their performances. It is also good to note that my answer to question 2a and 2b came from the use of Gradient Boosting regressor. Find below the details of the regressors I used and their various performances.

1. **Linear Regression:**

Performance of the Model on the train data.

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Performance of the Model on the validation data.

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1. **Ridge Regression:**

Performance of the Model on the train data.

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Performance of the Model on the validation data.

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1. **Lasso Regression:**

Performance of the Model on the train data.

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Performance of the Model on the validation data.

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1. **Random Forest:**

Performance of the Model on the train data.

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Performance of the Model on the validation data.

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1. **Gradient Boosting**

Performance of the Model on the train data.

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Performance of the Model on the validation data.

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Performance of the Model on the test data.

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Looking at all the regressors I used, they all have good R-squared and Adjusted R-squared. For the Linear regression, the R-squared and Adjusted R-squared are 0.817138 and 0.816555 respectively on the training while it is 0.808655 and 0.806191 respectively on the validation.

For my Ridge regression, the R-squared and Adjusted R-squared on the training and validation data are 0.817138 & 0.816555 and 0.808649 & 0.806185.

The Lasso regressor has R-squared of 0.81711 and Adjusted R-squared of 0.816527 on training. Its values for R-squared and Adjusted R-squared on validation are 0.808748 and 0.806285 respectively.

These models did well in both training and validation. However, I am interested in getting out the one with the best performance hence I tried the Tree based regressors or models.

For Random Forest, the performance on the model and test was powerful and better than the 3 mentioned earlier. The R-squared and Adjusted R-squared on training are 0.984682 and 0.984633 respectively while on validation it is 0.962915 and 0.962437 respectively.

My best among them all is Gradient Boosting. The Gradient boosting showed the highest generalization as even the performances experienced on the training, validation and test are very close when compared with other regressors. The R-squared on training, validation and test are 0.96304, 0.958508 and 0.964584 respectively while the Adjusted R-squared on training, validation and test are 0.962922, 0.957973, and 0.96422 respectively. The Gradient Boosting regressor gave me the best performance among all the 5 hence my choice of choosing it.

My reasons are summarized below:

1. Performance: Gradient Boosting performed better than all the models that I tried out.
2. Incorporation of feature importance attributes especially over Linear, Lasso and Ridge. These attributes helped me to pick out the top independent variables that best predict Global Sales.
3. Ensemble method: It combines the contributions of multiple weak learners to make final predictions thereby leading to a better performance than a single linear regression.
4. I benefited from its ability to perform feature selection because of my large data set especially after the One Hot encoding that expanded my dataset.
5. Ability to minimize loss function thereby reducing the impact of outliers.
6. Non-Linearity: This regressor can model non-linearity relationships between features and their target variable while linear regression only looks at the linear relationships between independent variables and their target variables.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| 1. **Use all the relevant categorical variables in the Video Game Dataset as the target variable at each instance and determine which of the variables performed best in classifying the dataset. Explain your findings.**   I used 3 categorical variables as the target each to determine which of the variable performed best in my classification. The 3 variables used are Rating, Genre, and Platform (Platformprimary). Below are my findings.   1. **Rating**   **Classification performance on training:**    **Classification performance on test:**    The variable ‘Rating’ did not perform well in classifying the dataset on training and test. On the training data, the values for accuracy score and recall are 0. 411424 and 0.269356, while that of Precision and F1-Score are 0.292527 and 0. 181459.This means that the classified model was able to make 29% correct predictions out of the total dataset. For the test data, the performance was 0.408656 for Accuracy, Recall - 0.265159, Precision – 0.249844 and F1-score – 0.174088. This showed that the model did not perform in both training and test.   1. **Genre:**   **Classification performance on training:**     |  |  | | --- | --- | | **Classification performance on test:**    The variable ‘Genre’ did not perform well in classifying the dataset on training and test. On the training data, the values for accuracy score and recall are 0.221565 and 0.086337 respectively. Those of Precision and F1-Score are 0.095741 and 0.035959. For the test data, the performance was 0.219426 for Accuracy, Recall - 0.083143, Precision – 0.018295 and F1-score – 0.02999. This showed that the model did not perform in both training and test. The Genre variable performed worse than the Rating variable.   1. **Platform (Platformprimary):**   **Classification performance on training:**    **Classification performance on test:**    The variable ‘Platform(platformprimary)’ did not perform well in classifying the dataset on training and test. On the training data, the value for accuracy is 0.372295 score and that of Recall is 0.226022. Precision is 0.138024 and F1-Score value is 0.149258. For the test data, the performance was 0.367388 for Accuracy, Recall - 0.223617, Precision – 0.136369 and F1-score – 0.147199. This showed that the model did not perform well in both training and test.  The Platform variable performed better than Rating and Genre. However, the performance is not good enough to be deployed to production or used as a predicting model.  I used macro averaging to aggregate the performance of all scores across multiple classes. This is because macro treats every class equally and for a non-complex data used in this classification model, macron seems ideal for me.  In summary, the model struggled to understand the pattern in the data. This is because the model finds it difficult to find how these features help it to predict the target variables.   1. **How did you check whether your models did not overfit?**   I checked this through the performance evaluation on my models.   * For all my regressors, they generalized well and did not overfit. The R-squared values (coefficient of determination), and Adjusted R-squared values are high on both training and validation (unseen data) and test with no significant difference in values between them on both training, validation, and test data. For example, in my gradient boosting, the R-squared on training, validation and tests were 0.96304, 0.958508 and 0.964584 respectively, while my Adjusted R-squared were 0.962922, 0.957973, and 0.96422 respectively. My model performed better in tests than even in training and validation. This showed that my model did not overfit. * For all my classifiers, the models underfit as they did not do well on both training and test data. The Accuracy, Recall, Precision and F1-score are low on both the training and test set. For my platformprimary(platform) variable. The values on the training are accuracy - 0.372295, Recall - 0.226022, Precision - 0.138024 and F1-Score - 0.149258. For the test data, the performance was 0.367388 for Accuracy, Recall - 0.223617, Precision – 0.136369 and F1-score – 0.147199. For the remaining classification that was done on Rating and Genre, all their scores are less than 0.45 which is less than 45%. This showed that the model did not perform well in both training and test, hence they UNDERFIT.  1. **Can your classification models be deployed in practice based on their performances? Explain.**   The models for classifications **cannot** be deployed in practice because they are not reliable. They are underfitting and underfitting models should not be deployed in practice.   1. **In the video game dataset, use a relevant categorical variable and other relevant noncategorical variables to form groups at each instance.** **By employing internal and external evaluation metrics,** **determine which categorical variable best describes the groups formed.**   Here, I selected 3 categorical variables of Genre, Platformprimary (Platform) and Rating to form a group each with non-categorical variables. The non categorical variables are NA\_Sales, Other Sales, EU\_Sales, and JP\_Sales.  Below are the different plots, internal and external evaluation results for each of them.  **Genre:**      External Evaluation Measures  \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*  V-measure Score: 0.064  Rand Index Score: 0.017  Mutual Information Score: 0.063  Internal Evaluation Measures  \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*  Davies-Bouldin Index: 1.043  Silhouette Coefficient: 0.374  Calinski Harabasz Score: 9977.554    The Genre reported poor classification after been evaluated with external evaluation metrics with V-measure of 0.064, Rand Index is 0.017 while the mutual information score is 0. 063.However, the internal metrics indicate that clustering is well defined. The Davies-Bouldin index is 1.043, Silhouette coefficient is 0.374 while Calinski Harabasz has a score of 9977.554. In summary, while the clustering is consistent, the external validation still needs improvement.  **Platformprimary (Platform):**      External Evaluation Measures  \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*  V-measure Score: 0.030  Rand Index Score: 0.024  Mutual Information Score: 0.029  Internal Evaluation Measures  \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*  Davies-Bouldin Index: 0.998  Silhouette Coefficient: 0.381  Calinski Harabasz Score: 10190.596  The Platformprimary (Platform) reported poor classification after been evaluated with external evaluation metrics with V-measure of 0.0030, Rand Index is 0.024 while the mutual information score is 0. 029.However, the internal metrics indicate that clustering are well defined. The Davies-Bouldin index is 0.998, Silhouette coefficient is 0.381 while Calinski Harabasz has a score of 10190.596. In summary, while the clustering is consistent, the external validation still needs improvement.  **Rating:**        External Evaluation Measures  \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*  V-measure Score: 0.064  Rand Index Score: 0.017  Mutual Information Score: 0.063  Internal Evaluation Measures  \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*  Davies-Bouldin Index: 0.934  Silhouette Coefficient: 0.393  Calinski Harabasz Score: 10701.493  The Rating reported moderate classification after been evaluated with external evaluation metrics with V-measure of 0.064, Rand Index is 0.017 while the mutual information score is 0. 063. The internal metrics indicate a better clustering. The Davies-Bouldin index is 0.934, Silhouette coefficient is 0.393 while Calinski Harabasz has a score of 10701.493 which indicates a dense and well separated cluster.  In conclusion, **Rating categorical variable** possess the most coherent clustering among the 3. This can be seen by its lower David- Boulding of 0.934 and a higher Silhouette coefficient of 0.393 which is an indication of a better intra-cluster similarity and inter cluster distance. A score of 10701.493 for Calinski Harabasz indicates that the clusters are distinct and well separated.  Similarly, Genre’s Davis-Bouldin index score is 1.043 which showed less cluster cohesiveness. The Genre’s Silhouette coefficient is 0.374 also indicates less cluster similarity within the clusters. The Platformprimary, with Silhouette coefficient of 0.381 and Davie-Boulding score of 0.998 indicates both lower intra-cluster similarity and cohesiveness than the Rating variable.  In summary, Rating is the best descriptor of the groups formed because it showed better inter cluster distances, intra cluster similarities and better cohesiveness.  **Conclusion:** This study showed that the best predictors of global sales of video game are sales in North America, Japan, EU and other sales. It also showed features like critical scores are a strong determinant of video game’s global sales. One take away from all the analysis carried out is that regressor tools like Linear regression, Lasso, tree based regressors like random forest and gradient boosting are good tools to analyze datasets like video game sales. When it comes to clustering without the numerical features, variables like ratings and user reviews may have some roles to play.  **TITELE HANDWRITTEN DIGITS REGOCNITION**  **Abstract:**  In this study, I investigated how to classify the MNIST dataset using convolutional neural networks (CNNs). With various architectures, regularization strategies, and learning rates, I constructed and trained several CNN models. The performance of each model was then assessed using accuracy, loss, and classification reports.  **Introduction:**  MNIST is a well-liked dataset that is utilized for image recognition and classification jobs. There are 70,000 grayscale pictures of handwritten numbers from 0 to 9, 60,000 of which are for training and 10,000 for testing. Due to their capacity to learn features directly from raw data without the need for manual feature extraction, CNNs are a popular choice for image classification jobs.  **Methodology:** To ensure that we obtain a good result, this project was done building a model with just one convolution block and regularization. That helped to track any difference in the performance of the model. After building the first model, the performance score was taking. The next step was tweaking the model by adding the L1 and L2 regularization. This followed by another tweaking of adding another regularizer which is the early stopping. The performance was observed and documented on Jupyter notebook. To guarantee consistent result, the same model was also tweaked to add another convolution block making it two convolution blocks with early stopping as a regularizer. The next step was tweaking the same model to 3 convolution blocks where the performance was observed and documented. The next step is to determine the performance of the model’s learning rates. This time around, L1 and L2 regularizer with different learning rates of 0.01 and 0.001 at different instances were used. In all, a total of 7 CNN models were built. Tools like python, google colab, Jupyter notebook were used to achieve this. The details and results are discussed in full details below.  **Results:**  A total of 7 models were built with different regularizers, convolution blocks, and two different learning rates to analyze the performance of CNN model at each instance. These models are listed and explained below.   1. **Model without Regularization:**       After 10 training iterations, the model without regularization has a validation accuracy of 0.9668. With an overall accuracy of 0.97, the classification report demonstrates great precision and recall levels for each class. The confusion matrix shows various misclassifications between classes that seem to be related, like 4 and 9. During training, the loss and accuracy curves exhibit good convergence and no overfitting. Overall, the model did a good job of correctly identifying handwritten numbers, although there is still space for improvement in terms of lowering misclassifications between related groups.   1. **Model with L1 and L2 Regularization**       On the training set and the validation set, the accuracy of the model with L1 and L2 regularization was 97.68% and 97.43%, respectively. This is somewhat less accurate than the model without regularization, which had a training set accuracy of 97.90% and a validation set accuracy of 97.77%. The L1 and L2 regularized model, on the other hand, has lower loss values on both the training and validation sets, suggesting that it is more accurate at generalizing to new data. Additionally, the precision and recall scores for the L1 and L2 regularized model are marginally higher for most of the classes, indicating that it is more accurate at classifying the various digits. As a result, while regularization could have somewhat decreased overall accuracy, it has increased the model's generalizability.   1. **Model with Early Stopping Regularization**       By monitoring the validation loss during training and interrupting the training process as the validation loss starts to climb, the Early interrupting Regularization technique is used to prevent overfitting in machine learning models. The training was stopped in the given model after 13 of the 20 epochs, yielding a 98.22% accuracy and a 0.0563 validation loss.  When the three models were compared, the model with Early Stopping Regularization fared better in terms of accuracy and precision than the other two models. In comparison to the model with L1 and L2 regularization (97.68%) and the model without regularization (92.79%), it attained an accuracy of 98.22%, which is somewhat higher. The Early Stopping Regularization model likewise had the highest precision values for all classes. **Model with 2 Convulation Blocks:** A picture containing text, screenshot, plot, line  Description automatically generated A picture containing text, plot, line, screenshot  Description automatically generated  A picture containing text, screenshot, number, font  Description automatically generated  The accuracy and f1-score of this model, which combines early stopping regularization with two convolution blocks, were both 0.99 for most of the classes, suggesting exceptional performance. Early halting was initiated at epoch 15 and the loss for the validation set rapidly decreased. The model properly predicted most of the test set samples, according to the confusion matrix.  The addition of a second convolution block improves the accuracy by 0.01 and the f1-score for most classes when compared to the prior model with early starting regularization and only one convolution block. However, as evidenced by the increase in time per epoch from 17 seconds to 36 seconds, the training period was longer. Consequently, while the additional convolution block enhances the model's performance, **Model with 3 Convulation Blocks:** A picture containing text, screenshot, line, plot  Description automatically generatedA line graph with blue and orange lines  Description automatically generated with low confidence  A screenshot of a graph  Description automatically generated with low confidence  The validation accuracy and weighted F1-score of the model with early stop regularization and three convolution blocks were 0.9927 and 0.99, respectively. In comparison to the model with two convolution blocks, this model is more accurate and has a higher F1 score. The model can learn more intricate characteristics and patterns in the data by using additional convolution blocks, which can enhance the model's performance. It is crucial to utilize methods like early halting regularization to avoid overfitting because adding additional convolution blocks may also raise the chance of doing so.  Based on the validation accuracy and F1-score, the model with three convolution blocks seems to perform better overall than the model with two convolution blocks. **Model with Learning rate of 0.01,3 convulation blocks, and L1 & L2 regularization.** A picture containing text, screenshot, plot, line  Description automatically generatedA picture containing text, diagram, line, plot  Description automatically generated  A picture containing text, screenshot, number, font  Description automatically generated  The accuracy of the second model, which included three convolution blocks, L1 and L2 regularization, and a learning rate of 0.01 was only 0.10, underperformed with a learning rate of 0.01. This might be because the algorithm overshot the ideal weights and got stuck in a less-than-ideal solution because of the high learning rate. The initial model had a substantially greater accuracy of 0.991 but no stated learning rate, unlike the model with L1 and L2 regularization. The CNN algorithm's performance can be significantly impacted by changing the learning rate, so it's crucial to experiment with and tune the learning rate to find the right value. **Model with 3 convulation blocks, L1 & L2 regularization and learning rate of 0.001.** A picture containing line, diagram, plot, slope  Description automatically generated A picture containing text, line, plot, screenshot  Description automatically generated  A screenshot of a computer  Description automatically generated with low confidence |  | | In comparison to the initial model without a learning rate and the model with a learning rate of 0.01 the model with three convolution blocks, L1 and L2 regularization, and a learning rate of 0.001 performed worse. With a learning rate of 0.001, the model's accuracy is only 0.09, and its precision, recall, and f1-scores are extremely low for most of the classes. This shows that the model cannot efficiently learn the characteristics of the photos because the learning rate is too low. In contrast, the initial models with and without learning rates had accuracy values of 0.91 and 0.1028, respectively. As a result, the model with a 0.01 and the one with learning rate of 0.001 performed poorly.  **Conclusion:**  I did notice some overfitting in some of the models. When a model performs well on training data but poorly on validation or test data, overfitting has taken place. When the model is overly complicated and has an excessive number of parameters in comparison to the size of the dataset, this is one of the main reasons of overfitting.  Overfitting was seen in the models that performed well on the training data but poorly on the validation data. For instance, a small overfitting was noticed in Model\_2 (early stopping regularization with one convolution block), which had a training accuracy of 0.9874 and a validation accuracy of 0.9824. The variance between the training and validation accuracy in this model was about 0.005, which is not very noteworthy.  However, there was a significant overfitting found in Model\_3 (Early stopping with two convolution blocks), which had a training accuracy of 0.9976 and a validation accuracy of 0.9828. The model was overfitting, according to the 0.0148 difference between training and validation accuracy, which is relatively large.  Overall, by limiting the model weights, regularization techniques like L1 and L2 regularization can aid in preventing overfitting in deep learning models. Additionally, keeping an eye on the model's training and validation accuracy can help detect overfitting and cause the model to be adjusted |  | |  |
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**COMPONENT 4.**

**Abstract:** This article review is about application of explainable AI (XAI) in AI in the field of financial industry. The article x-rayed the benefits of reliability, transparency, and ethics of using AI in the financial industry. It highlighted the challenges, benefits, gaps of XAI adoptions in the financial sector. It looked at how to address the gap between the banks and the supervisors in the position of authority on the requirements and scope of AI explainability under regulations and applicable laws. The result is that application of XAI can enhance fairness, accountability, and transparency in the financial industry.

**Introduction**: Financial industrial players have adopted the application of AI to achieve various financial goals. However, there are concerns and skepticisms among the practitioners with regards to the interpretability and transparency of complex AI models. The article **aims t**o address the risks associated with the usage of AI by x-raying the importance of applying explainable, reasonable, and trustworthy AI in the financial risk management sector. It also **aimed** to evaluate the application of XAI in financial planning. Another **aim** of this report is to investigate the supervisory authorities and bank’s perspective on the application and adoption of XAI in the financial sector.

**Methodology:**

Detailed literature search was implemented on databases like UniHull library, ResearchGate, and Acedemia.edu, applying keywords related to explainable AI in the Financial Industry. Three articles were selected, and data analysis was performed.

**Results:**

Some of the **contributions** are the provision of transparency, accountability, and interpretability of AI in financial risk management. The second **contribution** is the identification of key themes in research like the need for fairness and challenges that come will regulatory compliance. The use of explainable AI to predict regime changes in S&P 500 is one of the **contributions** in the field of XAI (Benhamou et al., 2021).

Fritz-Morgenthal et al., (2022) suggested that one of the **connections** between the themes in the context of AI adoption is the requirement for accountability and transparency in AI systems and the importance of ethical considerations while building the AI systems. Another **connection** is the need of XAI application which aids with decision making process and how to reduce or avoid the risks associated with the AI models. The third **connection** observed is the need for interpretability of AI and accuracy with regards to financial planning.

The **gaps** identified are lack of ethical consideration while building the AI systems, absence of standardization in XAI and the need to ensure bring human expertise into AI models. There is also lack of clear guideline and regulations of the requirements for explainable AI systems in the financial sector (Kuiper et al.,2023).

These **gaps need to be addressed** to ensure that there is no mistrust among the stakeholders and to avoid potential to consumers, humans, and society in general.

**Conclusion:**

In conclusion, I **recommend** tha**t** companies should collaborate with experts from different backgrounds to develop guidelines that are inclusive and culturally sensitive. I also **suggest** that practitioners to be involved in XAI model developments. Another **suggestion** is for regulatory bodies to come up with a clear guideline with regards to XAI systems

In all, XAI applications should be used to ensure the usage in the banking industry is fair, transparent, reliable, and trustworthy.

**List of Reviewed Articles:**

* Explainable AI (XAI) Models Applied to Planning in Financial Markets (Benhamou et al., 2021).
* Financial Risk Management and Explainable, Trustworthy, Responsible AI (Fritz-Morgenthal, et al., 2022).
* Exploring Explainable AI in the Financial Sector: Perspectives of Banks and Supervisory Authorities (Kuiper et al., 2022)

**Reference:**

Benhamou, E., Ohana, J.-J., Saltiel, D. and Guez, B. (2021) Explainable AI (XAI) Models Applied to Planning in Financial Markets. *SSRN Electronic Journal*, 102.2139(3862437).

Fritz-Morgenthal, S., Hein, B. and Papenbrock, J. (2022) Financial Risk Management and Explainable, Trustworthy, Responsible AI. *Frontiers in Artificial Intelligence*, 10.3389(12022.779799).

Kuiper, O., van den Berg, M., van der Burgt, J. and Leijnen, S. (2022) Exploring Explainable AI in the Financial Sector: Perspectives of Banks and Supervisory Authorities. *Communications in Computer and Information Science*, 10100/978-3-030-93842-0\_6(9783030938413), 105–119.

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