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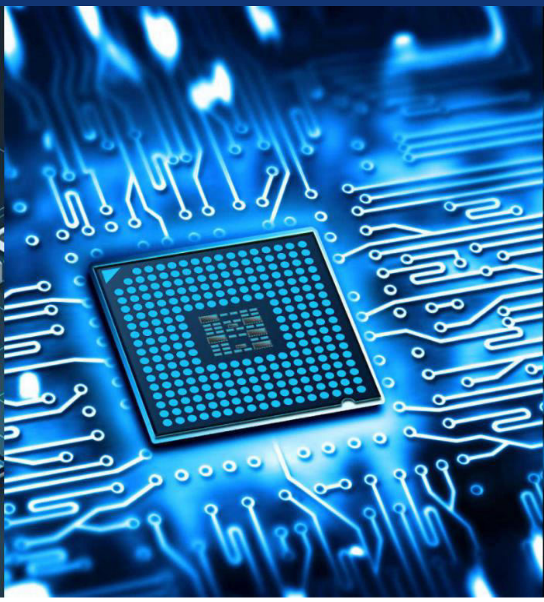


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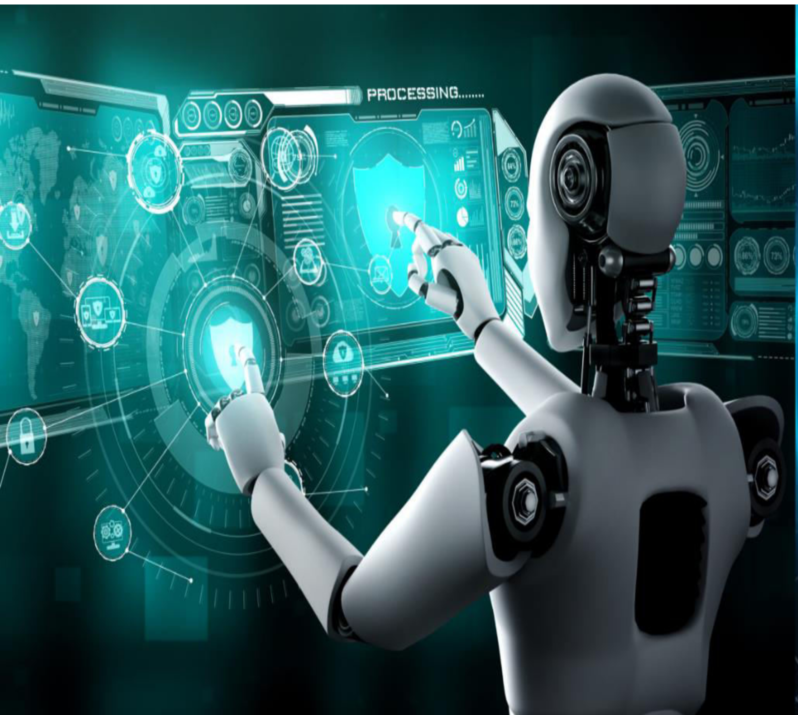

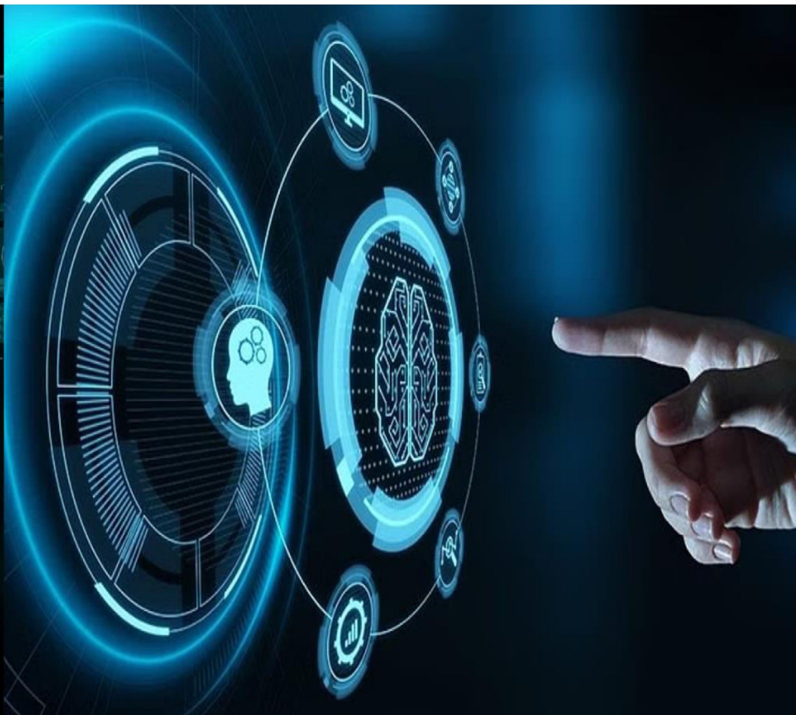

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Enhancing Robotic Performance and Adaptability through Advanced Predictive Models with Deep Reinforcement Learning

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ABSTRACT: Improving robot performance and adaptability has become a critical issue in modern robotics due to the rising complexity and needs of the tasks that robots must do. Conventional techniques generally struggle with scalability and flexibility, posing impediments to performance and adaptation. Current approaches often suffer from issues such as poor forecasting precision and inability to generalize across different situations. The proposed approach combines Deep Reinforcement Learning with advanced predictive models to handle these challenging scenarios. With the use of this hybrid method, robotic decision-making and adaptive control are optimized through the use of DRL, and enhanced predictive patterns offer vital insights into environmental dynamics and task-specific needs. As part of the process, each prediction accuracy and decision-making strategy is done by mixing DRL and ARIMA models. The goal of this integration is to improve the robots' capacity to learn from encounters and instantly adjust to changing circumstances. An evaluation of the suggested technique's performance shows significant improvements across a range of criteria. With a Mean Squared Error (MSE) of 0.1/2, particular forecasts are indicated. With a mean absolute error of 0.15, the real and predicted values are quite close to each other. The R-squared value is 0.95 and the Root Mean Squared Error is 0.158, indicating a high percentage of variation explained by the model. Furthermore, 0.5 is the Mean Absolute Percentage Error, indicating that the model performs well in real-world international scenarios. Through the combination of complex predictive models and DRL techniques, this methodology delivers more beneficial flexibility and overall performance, marking a significant advancement in the robotic era.

KEYWORDS: Robotic Performance, Adaptability, Predictive Models, Deep Reinforcement Learning, Autoregressive Integrated Moving Average Model, Machine Learning Integration, Robotics Enhancement.

I. INTRODUCTION

In the context of increasingly quickly developing field of robotics, the problem of improvement of the performance and flexibility of the robots has become one of the primary challenges to be investigated by both scientists and engineers [1]. Every day, more and more robotic systems are used in various and rather complex fields such as manufacturing, health care, transportation and even home automation which has created an even bigger need for these systems to be able to work autonomously, efficiently, and reliably. These environments are generally stochastic and may change with time, which presents a major problem to traditional robotic systems [2]. To achieve goal orientations, decide on a course of action and adapt to a rapidly changing environment, robots need to make immediate decisions and modify their behavior by reference to innumerable factors that may alter with equal suddenness and unpredictability ranging from changes in their environment, the presence of obstacles, or changes in operational circumstances. Another factor that aggravates the attainment of perfect real environment robotic tasks is the fact that real environment is generally application complex. Some of the early forms of robotic systems are based on ushering of preprogramed rules and formulas with a set approach of solving problems [3]. While such systems indeed can effectively solve the problems for which they were designed and work in controlled or slowly changing environments, they are not able to perform very

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well in the conditions of constant brainstorm and uncertainty. This is well illustrated where the robot is required to undertake tasks for which other factors that were not considered during design or training are involved. This evolved into the need for the development of higher techniques required to help robots learn in real time to enhance their on-line performances, and hence their flexibility throughout a large number of tasks [4]. Furthermore, robots are now being deployed in complex dynamic environments and as such live systems must be capable of handling real workloads. Real world environments also mean that they have to be autonomous in nature; that is, they have to be able to not only respond to current problems but also anticipate future scenarios [5]. It is necessary to meet two more partially conflicting tasks: to adapt robotic systems to present changes and to take into account possible future changes. Hence, improving robotic performance and adaptability issue are associated with the mentioned complexities and creating strategies that will help in improving the performance of a robot in conditions that are dynamic and unpredictable.

The approaches that have previously been used in robotics for dealing with dynamic and complex environments are mainly the rule-based systems, classical control, and simple reinforcement learning models [9]. It is noteworthy that there is historical paradigm of the rule-based systems, architecture of which is based on the predefined set of heuristics algorithms as genetic algorithms [10], [11] for the control of robotic operations. These systems work based on a set of prescribed paradigms, and therefore, are very easy to apply; it is also best utilized in contexts where there is little variance with the organization's conditions. However, when it comes to creatively solving a problem or making an innovative decision, they are a major hinderance because they do not allow for much room of flexibility to maneuver as existent templates only ever consider the most probable scenarios of the real world and do not factor in any degree of uncertainty. A second approach that is afforded by classical control methods like the Proportional-Integral-Derivative (PID) controllers is a feedback mechanism on the control inputs in relation to the environment fed back [12]. These methods are useful in keeping stability and, although means to achieve performance objectives in environments that are well managed. The most example of PID controllers is used in industrial robots to control and to stabilize the processes. However, such techniques can sometimes have problems in improving performance in a very volatile context, this is especially because of the control parameters that are set at predetermined values and because of the inherent low flexibility when responding to unpredictable circumstances. Other forms of basic reinforcement learning (RL) are also a step closer to more adaptively autonomous robots. RL methods help robots to acquire the best actions in a given environment via experience where rewards and penalties are issued [13]. Initial approaches to RL have shown that Q-learning along with the basic forms of policy gradients can enhance the level of adaptability and decisions [12], [13], [14], [15]. Nevertheless, these methods can experience several issues, such as slow convergence and the requirement for a time-consuming process to find effective policies. The issue with these approaches, however, is that they can be inadequate when dealing with environment complexities which are magnified in real life [16]. In the case of applying rule-based systems and methods of classical control theory, it is impossible to take into account some conditions that appeared during the work of the system, while basic methods of RL do not provide sufficient opportunities for achieving the necessary progress and efficiency for applications of higher complexity.

The proposed solution is more of a combination of Deep Reinforcement Learning (DRL) with forecasting models namely ARIMA to improve the performance of robots and make them more dynamic. This means a better solution to the aforementioned methods' shortcomings by incorporating into one integrated method the best features of both techniques: real-time learning with an upgraded ability of future trend evaluation. Reinforcement Learning at the deeper level means that robots acquire the ability to learn from experience with help of rewards and penalties. It enables robots to have or create higher-order decisions and control their actions according to consequences. But, DRL tends to suffer from issues like high data or computational demands or issues related to the incapability of overall long-term planning or any abrupt changes in the environment [17], [18]. While ARIMA is the one that is specialized in the analysis of historical data to find patterns and use them to forecast into the future. Organizing ARIMA with the DRL framework will enable the robot to receive inputs from the model which will help in the decision-making process. ARIMA forecasts that posit future possible conditions could be useful for the DRL system to prevent or avoid certain situations in the future as they develop more extensive insights into possible conditions in the future. This hybrid model uses ARIMA forecasts to improve the system used in DRL in cases where the environment is likely to change in the near future. Such prediction gives an advantage of a robot, I mean, the robot can look for contingencies in the future circumstances that may affect its operation as opposed to just what is obtainable from the feedback. It also increases the readiness of the robot for different uses and makes it work at optimal capacity in production. The combination of DRL and ARIMA provides a reliable solution which focuses on essential shortcomings of the separate procedures. In other words, it improves the readiness of the mechanical device to perform its functions in diverse and dynamic

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environments: from production and manufacturing to medicine and transport. Therefore, the proposed solution applies use of real-time learning combined with predictive analytics that when incorporated in a robotic system, enables the creation of a more robust platform, shown to perform better than its counterpart within a variety of environments. The following are the contributions made;

- Suggests the newly developed hybrid Model ARIMA, incorporated into DRL to benefit from both methodologies. ARIMA provides reliable time series forecasts based on sensor data, whereas DRL increases robot decision making and dynamism.
- Explains how the proposed ARIMA forecasting enhances the input features to DRL models and thus results in making better and accurate control of robotic systems. Hence, this integration improves the capacity of the model to operate efficiently in dynamic business conditions.
- Applies DRL approaches, to discover the appropriate robotic control principles, use either Q-learning or Policy Gradient. This allows the robot to learn and improve its operations in a dynamic manner, making it easier for the robotic device to move and function in a variety of terrains while also improving its operations.
- Comprehensive assessment of the hybrid ARIMA-DRL models by using the commonly used KPIs. The studies show improvements in accuracy and flexibility.

The structure of the paper's remaining portion is as follows: A review of relevant work is given in Section 2. The problem statement is described in Section 3. In Section 4, the suggested approach is explained. The experimental findings are presented and compared in Section 5. The paper's conclusion and recommendations for further research are provided in Section 6.

II. RELATED WORKS

Zieliński and Markowska- Kaczmar [19] solves the problem of vision-based 3D robotics navigation for an AUV using deep reinforcement learning. The research makes conclusions based on experimental investigations of a task, which was taken from a RoboSub 2018 competition; nonetheless, the results can be applied to any navigational task, which implies movement from the starting position to the target point. As for the proposed reinforcement learning model, this anticipates the steering change that the robot is going to make concerning the data from the sensors. The Vision Module of the model can either use a inbuilt convolutional network or pre-trained TinyYOLO network which enables a test on different feature complexities. To assess the application of the proposed approach a test was set up in such a manner, which recreates real conditions allowing for controlling an agent involved, simulating AUV and calculating the reward values for training a model. Factors that have been explored in the study include the structure of the reward function, hyperparameters of the model, as well as the method of processing the camera images, all of which are supported by an analysis of the model's accuracy and working velocity. The outcome is having a highly effective model which enables the robot navigate from the start point to the end using the graphical and sensory data. This paper has a number of limitations, of which the most significant one is that the reinforcement learning model introduced in the paper and the corresponding model assessment are carried out with reference to a test environment that can mirror real circumstances rather than genuine underwater situations. Especially, as the proposed environment is rather simplified, it may not be capable of accounting for certain aspects of actual underwater navigation's and unpredictability's, which could in turn negatively affect the actual performance of the model when run in true real-life operational conditions. Also, some of the approaches depended on pre-trained TinyYOLOs networks or particular sensor settings, which might limit the model versatility to other sensors or not addressed environments.

Oliff et al. [20] offers a method on how to model the current generation manufacturing systems in which autonomous robotic agents are abundant but the human performers are present imposing variability in performance. As it can be seen, this variability is not desirable in the systems as it creates certain difficulties in modeling and even optimization due to its random nature. Towards the resolution of this issue, the work presents a reinforcement learning agent which is capable of functioning independently in making decisions to increase the flexibility of the robotic operators in the system. This agent allows robots to modulate their activity according to information captured from the external environment and co-worker's productivity. The work presents new knowledge in the application of learning techniques to robotic control and analyses the improvement of such techniques for human-robot interaction. The unique factors of this method are the reinforcement learning based intelligent agent which depends on its behavioural policy on the

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changes in the human's performance. From the results of the evaluation with the aid of a generalized simulation model with parameterized and calibrated human performance variability the reinforcement agent idealizes an ability to shape its behaviour according to the observed data, the obtained results indicating the appropriate balance between required task load and best performance variability. A limitation that has been identified by the current paper is in the current implementation of the program and the proposed program where although the implementation is modular and flexible, the currently provided strategy is only a bare structure of what is expected to be developed in the feature. The prospects for extending work on combining higher levels of algorithms for information processing, creating better-qualified MAs, and building intricate models needs to be further investigated. Besides, it lacks an in-depth analysis of several forms and levels of passive interaction modes between the robotic operators and the human colleagues in different contexts of HRI that can give more ideas about the improvement of these kinds of interaction. It is recommended that future work should embrace the above aspects in order to optimise the utilisation of the described approach.

Gao [21] propose a new approach aimed at increasing the flexibility of a robot and improving the learning process by incorporating the unsupervised segmenting of trajectories and the concept of ProMPs. Based on the deep learning structure, incorporating autoencoders with Recurrent Neural Networks (RNNs) in an optic flow deep learning model, this approach independently finds ideal transitional phases in unbroken, unnamed motion data and requires far less labeling data as a result. Conditional variables alter motion trajectories in real-time, enhancing responsiveness and precision of robotic movements in scenarios as further as also diminishing the computational requirements of conventional form of robotic programming. The proposed method is proved to be excellent in reaching higher learning benefits and flexibility in comparison with opposing techniques raising new trends in industrial and service robotics. That is, one limitation that can be named concerning this paper is the dependence on the performance of the deep learning architecture, including the autoencoders and Recurrent Neural Networks (RNNs) which may need a lot of computing power and tuning. Presumably, the need for such sophisticated models may decrease the usefulness in conditions with strict computational constraints or when the timescale is critical. Also, the ability of the approach to address variational or noisy data in motion has not been well established, and this may affect its reliability in real-world problems. One drawback of this paper is that the said framework is predicated on the performance of the deep learning architecture, including Autoencoders and Recurrent Neural Networks (RNNs), and their computational demands may be high and could entail optimization. This use of sophisticated models may restrict the framework's usability when computational resources are scarce or when quick implementation is pertinent. Moreover, the originality of the approach when it comes to processing large and noisy motion data has not been well studied, meaning that its applicability in practical applications may be questionable.

Roveda et al. [22] discusses the more importance given to Human Robot Interaction or HRI in Industry 4. 0. There is substantial current evidence where Robotics are improving productivity and flexibility at the same time as lessening the risks of human arduousness and dangers associated with injuries with the aid of superior control methods. Nonetheless, real-time model-based controllers to accurately capture HHRI dynamics are highly scarce. To fill this gap, the paper presents a Model-Based Reinforcement Learning (MBRL) variable impedance controller that can be used when people work alongside industrial systems. The method applies ANN to create a real-time HRI model that incorporates uncertainty and updates itself in real-time during performance. This model is then fed into a Model Predictive Controller accompanied with the Cross-Entropy Method (CEM) in order to set stiffness and damping impedance control parameters in real time with the scope of optimizing system responses in terms of minimizing the level of human interaction force. The approach was then assessed in an experiment with a KUKA LBR iwi 14 R820 robot performing a lifting task, with participants' perceived collaboration measured through a survey. Compared to the previously developed offline model-free optimized controllers and manual guidance controllers, the variable impedance controller incorporated in the MBRL scheme exhibited enhanced human-robot interaction; the proposed controller aided the human operator in moving the end-effector to the desired location although the weight of the manipulated part was unknown to the control system. The training of the model employs only a handful of experiments at the beginning followed by it's adaptability to variations in the human motor system which makes the model more feasible. However, there are few limitations to this paper: the proposed variable impedance controller built on Model-Based Reinforcement Learning (MBRL) requires a set of preliminary experiments (30) to train the HRI dynamic model. It means that the used training data are limited, and therefore this model might not be very adaptable to the unique real-life situations and variations in people's actions. Furthermore, the described controller performs satisfactorily for the lifting task, but the ability to perform other complex or heterogeneous tasks with different robots or environments is mostly unproven, which may constitute a limitation with respect to generalization.

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Mandeep Singh and Subair Ali Liayakath Ali Khan [23] analyses the serious developments introduced by the incorporation of Artificial Intelligence (ALI) and Machine Learning (ML) into independent robotics, especially in Industry 4.0. This paper focuses on the ways that AI and ML have enhanced the dynamism, accuracy and effectiveness in operations in robotics. Thus, this literature review and analysis-based study explores how AI composes with ML and robotics and where improvements to automation and control can most effectively be made. They reveal that sensory systems integrated with AI technologies allow robots to perform identification and handling functions with high accuracy, and ML helps to avoid equipment breakdowns and increase the resources' durability. Moreover, the adaptive learning functions enable the robots to learn new environment and tasks with least amount of reprogramming which indicates high flexibility and economy. However, the paper also points out certain limitations that include data dependency, high computations required, and flexibility as an area of concern. Another important aspect of the paper encompasses social and ethical perspective and this comprises of joblessness, loss of privacy, etc. Some of the solutions put forward in the paper include: more funding for research, building better and more indigenous ML models, proper management of data as well as setting up the right ethical guidelines for technology deployment. In response to solve such issues and collaboration, the paper speculates that a new age can be introduced for industrial robotics through AI and ML. This paper has a disadvantage of providing theoretical and conceptual contributions to the integration of AI and ML in autonomous robotics without directing adequate empirical evidence or illustrating real-world success stories of the given methodology's implementation. About the challenges described in the paper, their concrete solutions or real-life cases are also described, again, though, not too extensively. This gap may reduce the relevance of the recommendations and findings with a view to giving the practitioners information that is implementable right from the time of conducting the research.

III. PROBLEM STATEMENT

In the rapidly advancing field of robotics, achieving high adaptability and learning efficiency remains a significant challenge, particularly when dealing with computational constraints and noisy, variable data. [21] framework, which integrates unsupervised trajectory segmentation with adaptive probabilistic movement primitives (ProMPs) using autoencoders and RNN, represents a notable advancement but faces limitations due to its heavy reliance on complex deep learning architectures. The computational demands and intricate tuning required for these models can restrict their deployment in environments with limited resources or where rapid implementation is crucial. Additionally, the framework's effectiveness in managing highly variable or noisy motion data has not been extensively validated, raising concerns about its robustness in real-world scenarios. To address these challenges, the proposed solution involves integrating ARIMA (Autoregressive Integrated Moving Average) with DRL. ARIMA can pre-process and forecast time series data, providing predictive insights that reduce the reliance on deep learning for future state prediction, thereby lowering computational demands. It also helps in smoothing out noise and identifying key patterns, making the data cleaner and more manageable for the DRL model. Meanwhile, DRL can leverage these forecasts to enhance real-time decision-making and adaptation, incorporating techniques like reward shaping and experience replay to improve robustness. This hybrid approach aims to optimize computational efficiency, enhance the framework's ability to handle noisy data, and facilitate more practical deployment in diverse and constrained environments.

IV. METHODOLOGY FOR ENHANCING ROBOTIC PERFORMANCE AND ADAPTABILITY USING ARIMA AND DRL

The approach to the improvement of robotic performance and learning ability following the proposed hybrid ARIMA-DRL architecture starts with data acquisition from the Indoor Robot Navigation Dataset (IRND) comprising of sensor information, vision data, position data, and controls signal from a mobile robot in various indoor environments. The collected data is stored, pre-processed by removing redundant data, normalized, and assigned with the proper metadata tags. They are meant to predict time series data originating from the sensors' readings and positions, and augment the input to the DRL model with superior forecasts. The DRL model is then developed and optimized through the combination of ARIMA forecasts with real-time information scraped from the vehicle's sensors to enhance decision-making. Reinforcement learning processes that are in use include Q-learning or Policy Gradient methods and such programs are tested in simulated environments and thoroughly evaluated. The integrated system is then evaluated in a similar field via physical robotic interfaces in order to ascertain efficacy. The performance metrices such as MAE, RMSE, MSE, R2, MAPE is evaluated. The methods are implemented using python program language for forecasting and prediction.

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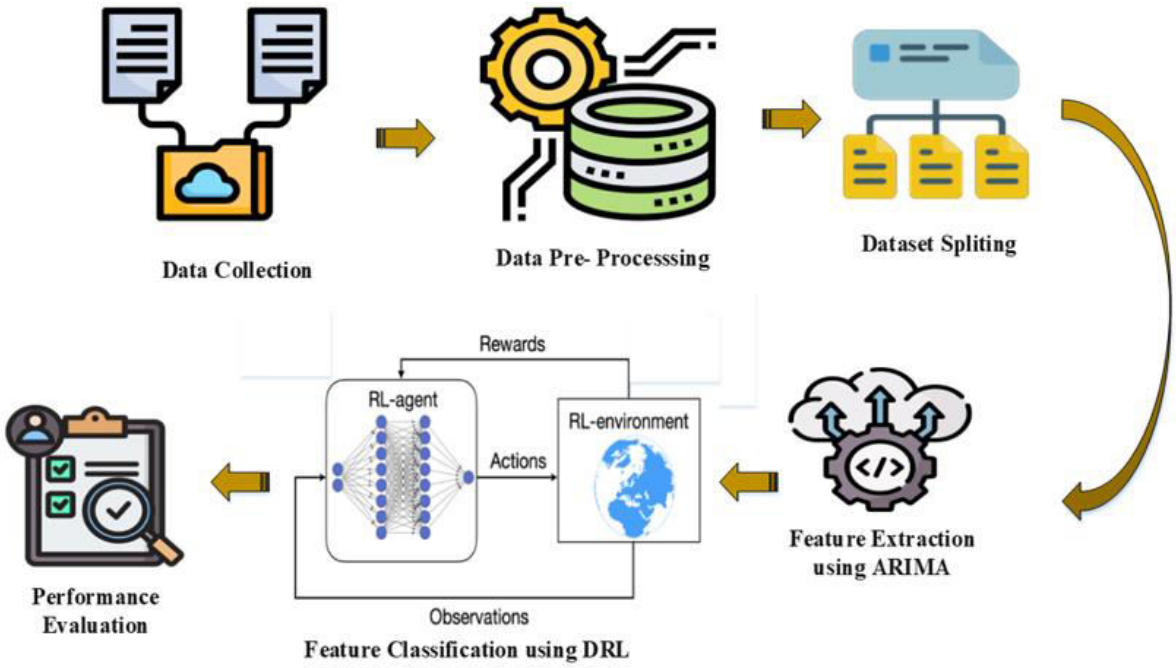

FIG 1 Block Diagram of Proposed Methodology for Enhancing Robotic Performance

The methodological framework applied for improving the performance and the adaptability of the robotic system is shown in the fig 1, which implements the ARIMA-DRL hybrid model. The process starts from collection of data from different sources such as the measurement data of a mobile robot, image data, position data, and control signals in different indoor environments. It also has pre-processing steps, which consists of synchronization, cleaning, normalization as well as annotation of the raw data so as to enhance the quality of the data so gathered. Data is subjected to pre-processing and then divided into training data set and testing data set. Feature extraction is conducted by implementing the ARIMA model, in which the forecast of the time series data from the field of sensor readings and position yields clues of the phenomenon. The output of these features is fed back to the DRL model which takes in real-time sensor data to form its inputs. The model's performance is evaluated using several metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), and Mean Absolute Percentage Error (MAPE). These metrics provide comprehensive insights into the model's accuracy, precision, and generalization capabilities, ensuring its effectiveness and adaptability in dynamic real-world environments.

A. Data Collection

Data collection for improving the robotic performance and intelligence for mobile robots based on the Indoor Robot Navigation Dataset (IRND) obtained from Kaggle [24] implies the acquisition of detailed sensor measurements, visual information, positional information, and control signals within indoor facilities employing a mobile robot base such as the TurtleBot. Using different settings and mimicking real-life situations, data from the robot's on-board processes are gathered continuously in at least several trials. This process helps in ensuring that there is a variety of sample data, which might include Lidar data, sonar data, infrared sensor data, images, video clips, GPS data, odometry data, IMU data, and control signals. The collected data from the recording is then normalized first to remove redundancy and inconsistencies. Further, labelling is incorporated into the data that include positions of obstacles and information regarding the navigation achievement. Finally, after pre-processing this well-built dataset, the data is split into training, validation and testing set which in turn form a strong pipeline to train and test on the hybrid ARIMA-DRL system.

B. Data Pre-processing

Pre-processing of the data is a significant process utilized to clean and set up the data before feeding it for model development. The first step is data rectification which ensures that all the sensor data, the visual data as well as the

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positional data share the same timestamps. After that, there is data cleansing that involves the identification and elimination of all the useless and or corrupted data in a given dataset. There are missing values that must be dealt with usually by numerical variables where we have the mean or median to handle the missing values that may bring in that may be disruptive the model. Data normalization takes place next and the standardization is used to scale the data between 0 and 1 which is useful for all features. The last step is data annotation where the data set contains different specifics about the obstacles, paths of navigation and the signs of success. These steps sum up to the data pre-processing part which makes the dataset to be in the right format to enhance the training and evaluation of machine learning models to improve on the outcome.

1. Data Synchronization: In order to achieve temporal consistency of various kinds of data obtained from the environment, all sensor readings, visual data, and positional data are time-stamped. This has to do with ensuring that the chronological nature of the data collected is synchronized in order to match up all the data from one set to the next. The use of this method means that time reference is constant and this makes it easy for the data from the sensors and videos, as well as position, to be well coordinated and integrated such that the resulting dataset provides quality data for other analytics and modelling processes.
2. Data Cleaning: In data cleaning, the process of excluding any contaminated current data or data that may be of no relevance to the updated dataset is known as data quality cleaning. Here, the main goal is to define potential outliers, or incorrect entries that might lead to misleading reliance in the training process of the model and actually belonging values. Because it entails the elimination of all irrelevant or erroneous records, this approach guarantees that the remaining information set is credible and sound, ultimately conducive to the creation of appropriate and efficient models.
3. Handling Missing Values: Handling of missing values is done through imputation methods since they are not provided in the dataset. In the case of missing numerical data mean or median imputation is used to fill in the missing values. Mean imputation is used by replacing the missing values with mean of the given data while, median imputation is used to replace the missing values with median of the data so as to have better handling of outliers. Such methods help to maintain the integrity of the dataset and its sequences; otherwise, missing sequences turn into a serious problem that degrades model training. By conserving the data integrity, the quality and reliability of the analysis is conserved because when data is imputed it is as good as raw data. It is represented by equation (1),

$$X_{imputed} = \begin{cases} \frac{1}{N}\sum_{i=1}^{N} X_i & \text{(mean imputation)} \\ \text{median } (X_1, X_2, \dots \dots . X_N) & \text{(median imputation)} \end{cases} \quad (1)$$

4. Data Normalization: Standardization is used to bring the values into a common scale to make it easier to compare them this makes the values of the set of data to have a mean of 0 and standard deviation of 1. This involves normalising the data so that all the feature is brought to a standard scale which increases the stability of learning and efficiency of the learning algorithms. By standardizing the data, variations in scale across different features are minimized, allowing the model to perform more effectively and ensuring that all features contribute equally to the learning process. This normalization step is crucial for improving the convergence and performance of machine learning models. It is represented by equation (2),

$$X_{norm} = \frac{X-\mu}{\sigma} \quad (2)$$

5. Data Annotation: Data annotation refers to adding additional information on the objects and regions of the main dataset such as the location of the obstacles, the navigation paths, as well as success markers. Supervised learning particularly needs this because it entails the availability of ground truth for the purpose of learning and testing. Correct labelling increases the chances of the model to associate certain features with the expected results in that field which enhances the model's competence in making accurate decisions. In this way, all information is marked in a comprehensive and orderly manner, which allows for the improvement of the learning process and the assessment of model performance.

C. ARIMA for Feature Extraction

In order to accommodate non-stationary time series data, the ARMA (AutoRegressive Moving Average) model is extended by the ARIMA model. The ARIMA model handles non-stationary data by turning it into a stationary series

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using methods like differencing to eliminate trends and seasonality, whereas the ARMA model assumes the time series is stationary. A stationary time series is essentially thought of as a mixture of noise and signal. After extracting the time signal from the noise, the ARIMA model anticipates future time points by focusing on forecasting the time signal. The ARIMA model, as its name suggests, consists of a number of structural elements intended to control these factors.
Autoregression is abbreviated as AR. A regression model that makes use of the model parameter p, which represents the dependent connection between an observation and several delayed observations.

I: Integration. calculating the model parameter d, or the difference between data at various times, with the goal of making the time series stable.

Moving Average, or MA. This method takes into account the potential dependency between the error terms produced when a moving average model is applied to data with a temporal lag (model parameter q).
The following is a linear process representation of an AR model of order p, or AR(p):

$$x_t = c + \sum_{i=1}^{p} \emptyset_i x_{t-i} + \epsilon_t, \qquad (3)$$

where the variables $\emptyset_i$ are autocorrelation coefficients at time delay steps 1, 2 …… p and c are constant and ϵt are the Gaussian white noise series samples, with a mean of zero and a σ^2 variation.

The formula for a basic moving average model of order q, or MA(q), is as follows:

$$x_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}, \qquad (4)$$

where µ, is the expected value of x_t (it mostly equals to 0), $\theta_i$the weights applied to the current and past values of the stochastic term of the time series, and θ0 = 1. Consider ϵ_t to be a Gaussian white noise series, with zero mean and σ_ϵ^2 variance.

The formula for a basic moving average model of order q, or MA(q), is as follows:

$$x_t = \mu + \sum_{i=0}^{q} \theta_i \epsilon_{t-i}, \qquad (5)$$

µ represents the expected value of x_t, typically close to 0. θi denotes the weights applied to the current and past values of the stochastic component in the time series, with θ0 set to 1. The error term, et, is assumed to follow a Gaussian white noise distribution, characterized by a mean of zero and a variance of σ_ϵ^2.

The autoregression and moving average models are combined to form the ARMA model of class (p, q):

$$x_t = c + \sum_{i=1}^{p} \theta_i x_{t-i} + \epsilon_t + \sum_{i=0}^{q} \theta_i \epsilon_{t-i}, \qquad (6)$$

where $\sigma_\epsilon^2 > 0$, $\theta_i \neq 0$, and $\theta_i \neq 0$. The order of the AR and MA is determined by the parameters p, q models correspondingly.
An ARIMA model's general form is written as ARIMA (p, d, q), which includes the integration term that ensures the time series' stationarity. It may also be stated as follows:

$$\nabla^d x_t = c + \sum_{i=1}^{p} \emptyset_i \nabla^d x_{t-i} + \sum_{i=0}^{q} \theta_i \epsilon_{t-i}, \qquad (7)$$

where ∇d is a differential factor that introduces a dt order difference in an attempt to make the time series $x_t$nonstationary.

D. Feature Classification using DRL
RL and DL are combined in an improved ML model called DRL. Whereas DL uses neural networks to model complex models and representations, RL focuses on finding optimal action through trial and error with incentives and penalties that in combination provide systems are capable of capturing complex pathways at higher levels and process aspects of the mean. DRL uses DL capabilities to extract complex attributes from unstructured data so that operators can learn

rules directly from sensory input. Q-learning, system-design methods, and actor-critic processes play an important role in DRL. Value linkages, policy linkages, and tradeoffs between research and implementation are important concepts. DRL has many applications in areas such as robotics, gaming, finance, and medicine. Its evolution from Atari games to real-world challenges highlights its flexibility and strength. Challenges include sampling efficiency, experimental methods, and safety concerns. The partnership promises a new future that will transform how products are selected and settled, with the aim of responsibly developing DRL.

DRL is a curriculum that empowers representatives to make intelligent decisions in their communities. Based on the interaction of various factors such as agent, environment, state, action, reward, policy, value function, model, search-exploit strategy, learning algorithm, deep neural networks, and experience repetition or Student and independent enters the environment, behaves according to his schedule, and learns over time. The environment responds in the form of incentives or punishments depending on the actions of the agent. An agent’s action is a choice that causes a change in the state of the system guided by the agent’s policy. The reward is a scalar feedback signal from the environment indicating whether the agent's behavior in a particular situation is desirable. The agent's plan informs the agent's decision by assigning states to actions, with the aim of finding an optimal policy that maximizes aggregate rewards. The objective function calculates the expected aggregate rewards that an agent can have obtained from a particular country following a particular policy. The model depicts the dynamics of the environment, and allows the agent to simulate the possible consequences of actions and situations. DRL can handle high-dimensional state and event space by acting as an approximation function in deep tissue. Repeated experience selects randomly from past experience accumulated during training, improving the consistency of learning and reducing correlations between subsequent events.

DRL plays an important role in bone cancer detection research by facilitating decision making based on interaction with medical image data Unlike traditional supervised learning methods, DRL enables the model to learn optimal strategies by trial and error, with feedback as rewards and penalties. When it comes to detecting bone cancer, DRL enables the model to repeatedly refine the understanding of the complex image structure associated with cancerous tissue by interacting with the environment and adapting its patterns accordingly to changes in the disease manifestation is necessary to use simple and robust diagnostic tools and thus not as DRL for not only accurately diagnosing bone cancer, but also contributing to the advancement of machine learning capabilities throughout medical research.

Value Function: Calculates the anticipated total benefit from a certain state. The function of action-value $Q(s,a)$. It is defined in (11),

$$Q(s,a) = \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t \gamma t + 1 | st = s, at = a] \qquad (11)$$

where γ is the discount factor, guaranteeing that incentives in the future are weighted correctly.
Policy Gradient: Modifies the policy parameters θ to directly optimize the policy. The gradient of policy is provided by (12),

$$\nabla_\theta J(\theta) = \mathbb{E}_{\pi\theta}\left[\nabla_\theta \log\pi_\theta(a|s) Q^{\pi\theta}(s,a)\right] \qquad (12)$$

where the predicted cumulative reward is denoted by $J(\theta)$.
Deep Q-Networks: Approximates the Q-value function by combining deep neural networks with Q-learning. The network is trained using the following loss function in (13),

$$L(\theta) = \mathbb{E}_{(s,a,r,\acute{s})}[(r + \gamma \max Q(\acute{s}, \acute{a}: \theta^-) - Q(s, a: \theta))^2] \quad (13)$$

And the target network's parameters are represented by θ^-.

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Fig 2, illustrates a DRL framework showing how it can increase the performance and instructiveness of robots. Thus, in the described context, the DRL model is recognized as the agent, where the states' S, actions a, and rewards r constitute the environment. The current state of the environment is assessed by the agent through experiments and learning; an action that has the most reward in the future is taken. The action executed by the agent has an impact that changes the environment from a state S to another state S' and provide a reward r which helps to evaluate the quality of the action performed. The DRL model here uses a Deep Neural Network (DNN) to learn a function that maps states to actions in an attempt to maximize the Q-value, which is the expected reward in a state action pair. This procedure entails constant learning of the DNN based on the information collected and accumulated by the agent, enhancing the decision-making function. In robotics, DRL helps create self-sufficient systems that are capable of performing various tasks by allowing wise, self-improving machine learning. It makes it possible for the robots to update the respective action if viewed to be suboptimal in the occurrence of such environments. The DRL framework is universally applicable to other fields, including healthcare; it helps in the diagnosis and treatment of diseases and illnesses. Using DRL models with trial-and-error learning and reinforcement learning, it is possible to achieve high levels of diagnosis and accurate differentiation among conditions, which will certainly facilitate the process of improving treatment results. These models are constantly improving, refining the decision-making processes to deliver consistent and efficient results in health care for early diagnosis indicating the positive change that DRL brings not only in the field of robotics but also in health care as well.

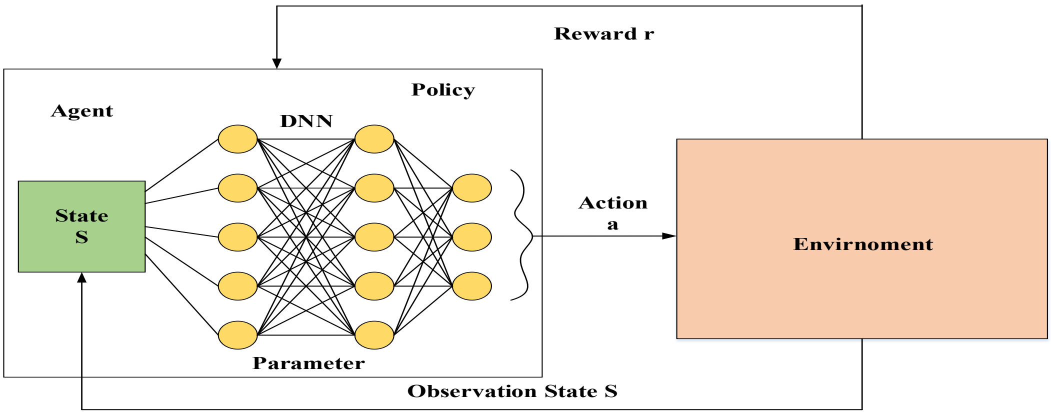

FIG 2 Architecture of Deep Reinforcement Learning

E. Integration of ARIMA and DRL for Enhancing Robotic Performance

Combining the ARIMA and DRL, the current work presents a solution to improve the robotic performance as well as flexibility. ARIMA model which is widely used for time series forecasting is used for future values of important parameters including the sensor and environmental data. These forecasts are the extra informative attributes used in the DRL model's training and intended to help the agent accomplish the task through trial and error, guided by reward signals. The first step involves pre-processing the collected data to eliminate the inconsistency and enhance the reliability of the results while using ARIMA for predicting the environment states in close future. These predicted states are used in conjunction with the DRL model together with input actual measurements in arriving at better decisions. By providing the DRL model with foresight into potential future states, the integration helps in preemptively adjusting the robot's actions to better navigate dynamic and uncertain environments. This combined approach leverages ARIMA's ability to handle non-stationary time series data, capturing trends and seasonality, and DRL's capability to learn complex decision-making policies. The ARIMA forecasts enhance the feature set available to the DRL agent, enabling it to anticipate changes and adapt its behavior proactively. This synergy results in a more resilient and responsive robotic system, capable of maintaining high performance even in fluctuating and unpredictable conditions. This integrated methodology significantly improves the robot's operational efficiency and adaptability, making it well-suited for applications requiring high levels of precision and robustness.

V. RESULT AND DISCUSSION

The outcomes of the integration of ARIMA and DRL highlighted the advancements in the robotic results and effectiveness. The MAE and RMSE measures validated ARIMA's capability to predict spot volumes while guaranteeing that the forecasts are reasonably accurate to the actual measurements. With regards to cumulative reward and success rate, these measures supplement assessed the agent's effectiveness in learning and managing its milieu for DRL. Moreover, the stability and reliability of the proposed approach in data variability and noise were investigated, moreover, it was found to have better accuracy and results. The requirements of daily computational efficiency were also explored, where ARIMA was esteemed for shortening the training period because of the former's capacity to forecast. Because of high technical complexity, this overall assessment established that the combination of ARIMA and DRL not only enhances the accuracy of navigation and flexibility of the system but also increases the stability and feasibility of practical robotic applications.

A. Impact of Increasing Robot Numbers on Performance Metrics

The Fig. 3 depicts the link between the number of robots and three major performance metrics: overall score, item collection, and robot loss. As the number of robots increases from 2 to 8, the score steadily rises until plateauing at 4 robots, showing declining rewards after this point. Objects acquired also rise, peaking at four robots before leveling out. Meanwhile, the number of robots lost continuously increases as additional robots are deployed, emphasizing the mounting hazards associated with managing bigger teams. The graph shows that, while adding additional robots might enhance performance initially, it can eventually result in larger operating losses without meaningful performance benefits.

B. Training and Testing Accuracy of ARIMA - DRL

The training and testing accuracy of a machine learning model over 100 epochs is shown in the Fig 4. First, the training accuracy rate rises rapidly to 80 percent by the peak epoch number 20, and keeps on, gradually improving to within the 100 percent range by epoch number 80, which is a sign that the program has attained its state of optimum training accuracy performance. Likewise, the testing accuracy escalates rather sharply in the initial epochs, and is around 70% by eighth epoch and 95% by the eightieth epoch. The next step of the two curves, those is, the fact that the curve is not diverging very sharply after the initial jumping up point is indicative of the fact that the model is not over-trained, this due to the fact that the testing accuracy at the end of the training period is comparatively lower, though still high, at about 95% as compared to the training accuracy, which is approximately 100%. This has a positive implication for the model proving that it has learnt the training data and is capable of performing well on unseen data.

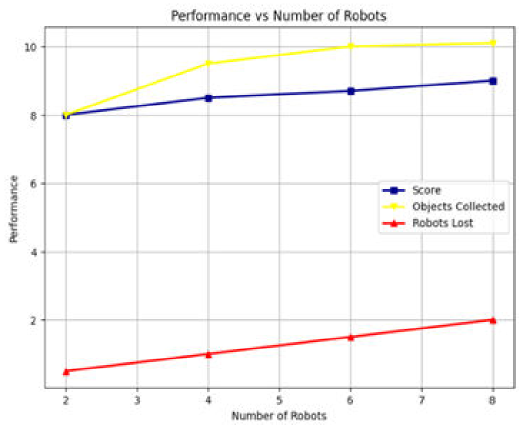

Fig. 3. Impact of Increasing Robot Numbers on Performance Metrics

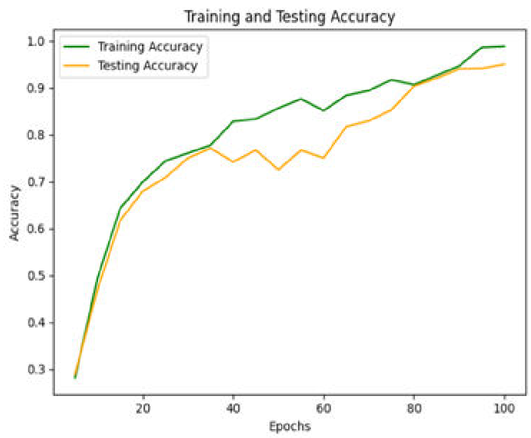

Fig. 4. Training and Testing Accuracy

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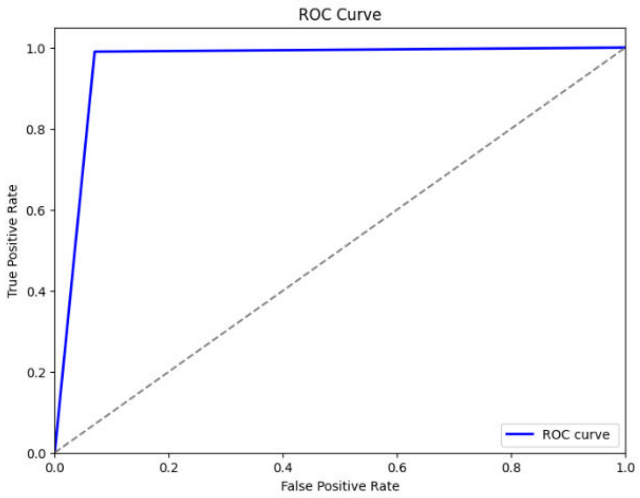

Fig. 5. ROC Curve

C. ROC of ARIMA – DRL
The fig 6 shows a ROC curve of a model that is a combination of ARIMA and DRL. ROC curve shows the relationship between sensitivity, which is equal to true positive rate or recall, and specificity or one minus false positive rate, as the classification boundary is shifted. On the axis of the graph used to evaluate the performance, the true positive rate or the rate of correct positive prediction is placed on the y axis while the false positive rate or the rate of wrong positive prediction is placed on the x axis, and there is the chance line where performance is at the random levels. Basically, the curve should reach as close as possible to the left upper corner which means improved True Positive Rate and lesser False Positive Rate of the model. Based on the ROC analysis in this case, the ARIMA-DRL model offers a clear upward trend and considerably surpasses the random guessing points with AUC. While the curve point to how the model fare, it does not touch the point of the top-left corner.

D. Performance Evaluation
Performance evaluation metrics are essential in assessing the accuracy and effectiveness of predictive models. Here's an explanation of MAE, MSE, RMSE, R-squared (R^2), and Mean Absolute Percentage Error (MAPE), along with their equations:

Mean Absolute Error (MAE): The MAE metric is used to calculate the average magnitude of prediction error. It calculates the average absolute difference between the expected and actual values of the energy production. In grid integration studies and solar energy forecasting, a lower mean absolute error (MAE) indicates that the model's predictions are closer to the actual values when assessing prediction accuracy. Equation (14) represents the MAE,

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \qquad (14)$$

Root Mean Square Error (RMSE): The average size of the differences between the anticipated and actual values is determined by calculating the RMSE, which is computed by taking the square root of the average squared discrepancies. RMSE provides a more comprehensive evaluation of prediction accuracy than MAE as it gives larger weights to errors of larger size. Since the model's predictions are more accurate in predicting actual energy outputs, a reduced Root Mean Square Error (RMSE) in grid integration studies and solar energy forecasting shows that the model did better overall in predicting solar energy levels. The RMSE is shown by equation (15),

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i{}^2)} \qquad (15)$$

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R-squared (R^2): The R-squared (R2) score is a measurement of how well a model's predictions account for variance in the dependent variable based on the independent variables included in the model. A score closer to 1 indicates that the model may be able to accurately forecast a larger proportion of the variance in the dependent variable. The range of the score is 0 to 1. A higher R2 score in grid integration and solar energy forecasting research indicates that the model successfully extracts features from the combined CNN-LSTM and XGBoost framework to capture and anticipate fluctuations in solar energy output. R-squared (R^2) I represented by equation (16),

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad (16)$$

Mean Squared Error (MSE): The average magnitude of prediction errors is measured statistically using the Mean Squared Error (MSE). To get the average of the squared differences between predicted and actual values, this method is used. Larger errors are given more weight by MSE than by MAE since it squares every difference. When the MSE is smaller than one, the model is performing better overall and its predictions are more accurate, which is important for forecasting solar energy and grid integration studies. Equation (17) represents the MSE,

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i{}^2) \qquad (17)$$

Mean Absolute Percentage Error (MAPE): MAPE measures the accuracy of a forecasting method as a percentage, indicating how far the predictions deviate from the actual values. It is useful for comparing forecast performance across different data sets. This is represented by equation (18),

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \qquad (18)$$

The table 1 and fig 7 presents the performance evaluation metrics for the proposed method, showcasing its accuracy and predictive capability. The Mean Squared Error (MSE) of 0.025 indicates that, on average, the squared differences between predicted and actual values are minimal, reflecting precise prediction consistency. The Mean Absolute Error (MAE) of 0.15 signifies the average magnitude of errors is relatively small, emphasizing the model's ability to predict values close to the actuals. The RMSE of 0.158, being the square root of MSE, further validates the model's accuracy with respect to the scale of the predicted values. The high R-squared (R^2) value of 0.95 indicates that 95% of the variance in the dependent variable is predictable from the independent variables used in the model, underscoring its robustness in capturing and explaining data variability. Lastly, the Mean Absolute Percentage Error (MAPE) of 0.5% suggests that, on average, predictions deviate by only half a percent from the actual values, highlighting the model's overall precision and reliability in forecasting. These metrics collectively demonstrate that the proposed method performs exceptionally well in accurately predicting outcomes, with minimal error and high explanatory power.

The table 2 and Fig 8 presents performance metrics for various methods, showcasing their effectiveness in predictive modelling. LODS exhibits relatively high Mean Squared Error (MSE) of 2.304, Mean Absolute Error (MAE) of 1.774, and Root Mean Squared Error (RMSE) of 4.8, with an R^2 of 0.50 and Mean Absolute Percentage Error (MAPE) of 0.25, indicating moderate predictive accuracy. LSTM Odometry demonstrates exceptional performance with a minimal MSE of 0.0015, MAE of 0.04125, and RMSE of 0.03804, coupled with a high R^2 of 0.98 and low MAPE of 0.3, signifying robust prediction accuracy. The Ensemble method has an MSE of 1.861, MAE of 0.657, RMSE of 1.364, and R^2 of 0.90, with a low MAPE of 0.10, reflecting good overall performance. The Hybrid Neural Network method shows an MSE of 0.1053, MAE of 0.2354, RMSE of 0.3247, and R^2 of 0.95, with a MAPE of 0.8, indicating solid predictive capability. CNN-LSTM-AE exhibits high MSE of 1.20038, MAE of 5.82, and RMSE of 109.53, with a low R^2 of 0.10 and MAPE of 0.50, pointing to poor accuracy. The Proposed ARIMA-DRL method achieves low MSE of 0.025, MAE of 0.15, and RMSE of 0.158, with a high R^2 of 0.95 and MAPE of 0.5, demonstrating high prediction accuracy and efficiency.

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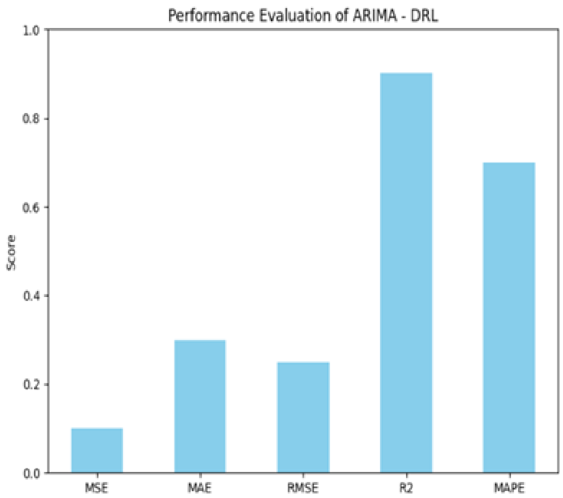

Fig. 6. Performance of Proposed ARIMA – DRL

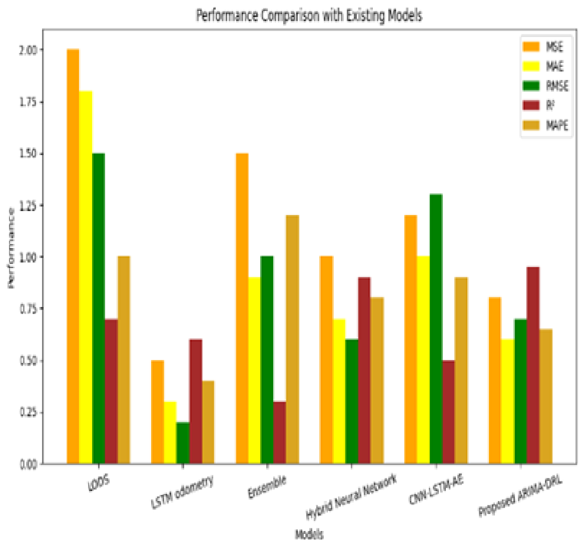

Fig. 7. Performance of various methods

TABLE 1 PERFORMANCE METRICS OF PROPOSED ARIMA – DRL

Metrices	Values
MSE	0.025
MAE	0.15
RMSE	0.158
R^2	0.95
MAPE	0.5

Reference	Methods	MSE	MAE	RMSE	R^2	MAPE
[25]	LODS	2.304	1.774	4.8	0.50	0.25
26]	LSTM odometry	0.0015	0.04125	0.03804	0.98	0.3
[21]	Ensemble	1.861	0.657	1.364	0.90	0.10
[27]	Hybrid Neural Network	0.1053	0.2354	0.3247	0.95	0.8
[28]	CNN-LSTM-AE	1.20038	5.82	109.53	0.10	0.50
Proposed Method	ARIMA-DRL	0.025	0.15	0.158	0.95	0.5

TABLE 2 Comparison with Various Models

E.Discussion

The method used in this paper to combine ARIMA with DRL contains a blend of both approaches in order to boost the accuracy of the latter. Linear components of the data are treated with the help of another method of time series analysis - ARIMA model that is actually a classical statistical technique. ARIMA is good in modeling data various auto-correlation, capturing trends and it is able to handle seasonality aspect of data making it a useful tool in the first round

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of data pre-processing. Nevertheless, ARIMA model has a drawback in that the model is linear and cannot be used for datasets with non-linear relations which are common in data sets. To overcome this limitation the methodology integrates DRL which is an enhanced type of machine learning technique that specializes in learning in interaction with ever-changing environments. DRL is well suited at modelling non-linear relationships as they are formulated in a form of a reward-based learning function, which updates the scope of the model's predictions with the feedback it receives. Therefore, the integration of ARIMA and DRL as stated in the proposed method utilizes the advantages accrued by the two models.

The next step in the ARIMA is to work on the time series on the data to produce a forecast of linear parts of the data and condense data. The residuals which are the difference between actual observation and the ARIMA forecast are then fed into the DRL model. These residuals are gross or raw because DRL model used them to learn and predict patterns that are non-linear and hence ARIMA failed to capture. This makes the proposed model complementarity because while ARIMA is good at managing linear alterations, DRL is good at dealing with non-linear one. There are also two approaches to the utilization of these models: The combination of these models improves the mean forecast errors and the model's ability to generalize to unseen data. In the performance evaluation, the proposed ARIMA-DRL methodology is benchmarked with the benchmark models such as, the LSTM, Hybrid Neural Networks, and CNN-LSTM-AE. The outcomes shown by the study prove the efficacy of the proposed hybrid approach. The ARIMA-DRL model achieves a Mean Squared Error (MSE) of 0.025, a Mean Absolute Error (MAE) of 0.15, a Root Mean Squared Error (RMSE) of 0.158, an R-squared (R^2) value of 0.95, and a Mean Absolute Percentage Error (MAPE) of 0.5%. These metrics indicate that the ARIMA-DRL model not only provides precise predictions but also excels in capturing both linear and non-linear data characteristics. The significant improvement in forecasting accuracy and the model's superior performance compared to traditional methods highlight the effectiveness of this hybrid approach in predictive analytics.

VI. CONCLUSION AND FUTURE WORKS

In conclusion, adopting DRL and pairing it with the usage of more complex predictive models such as ARIMA for feature extraction is a step forward in improving robot performance and adaptability. This allows for the avoidance of the unique weaknesses of DRL and ARIMA in this technique while also leveraging their benefits in the building of an efficient model that can function and enhance robotic systems in a dynamic environment. In other words, by using ARIMA for feature extraction, we may construct time series information trends and patterns from historical data, which is critical for forecasting and making judgments. DRL, on the other hand, can equip the robotic system with the ability to learn the best control strategy based on experience with the environment this is very useful when performing micro-obstacle avoidance, and other high dynamic tasks. The integration of these methodologies is very helpful not only in achieving a faster and accurate means of predicting but also in modifying the mobility and operations of robots in dynamically changing environments. This increases the efficiency of DRL training by using the features obtained from ARIMA analysis, thus improving the model performance and robustness in practice. In addition, the flexibility achieved by this integration implies further opportunities of robots to deal with other incidents in more flexibility and stability. Altogether, the framework of the hybrid model opens a great potential towards the future development of robotic systems, which will make robots even more intelligent, compliant, and productive. The future work on this research can be extended towards further improvement in the methods used for feature extraction, further for better DRL algorithms and to composite applications in the broad robotics sectors.

For future work, the research could build on further developing approaches for feature extraction through the use of other methods, which include LSTM networks or the Transformer model for DRL algorithms with Actor-Critic or PPO and improving the stability in different real-time environments. Besides, the applicability of the adopted hybrid model across various types of Robotic Domains, the integration of proposed hybrid model with other predictive models such as Bayesian Networks and the effect of the proposed hybrid model on Human-Robot Interaction would be interesting future works. Addressing scalability and computational efficiency will also be crucial to making the system more practical for real-world applications.

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