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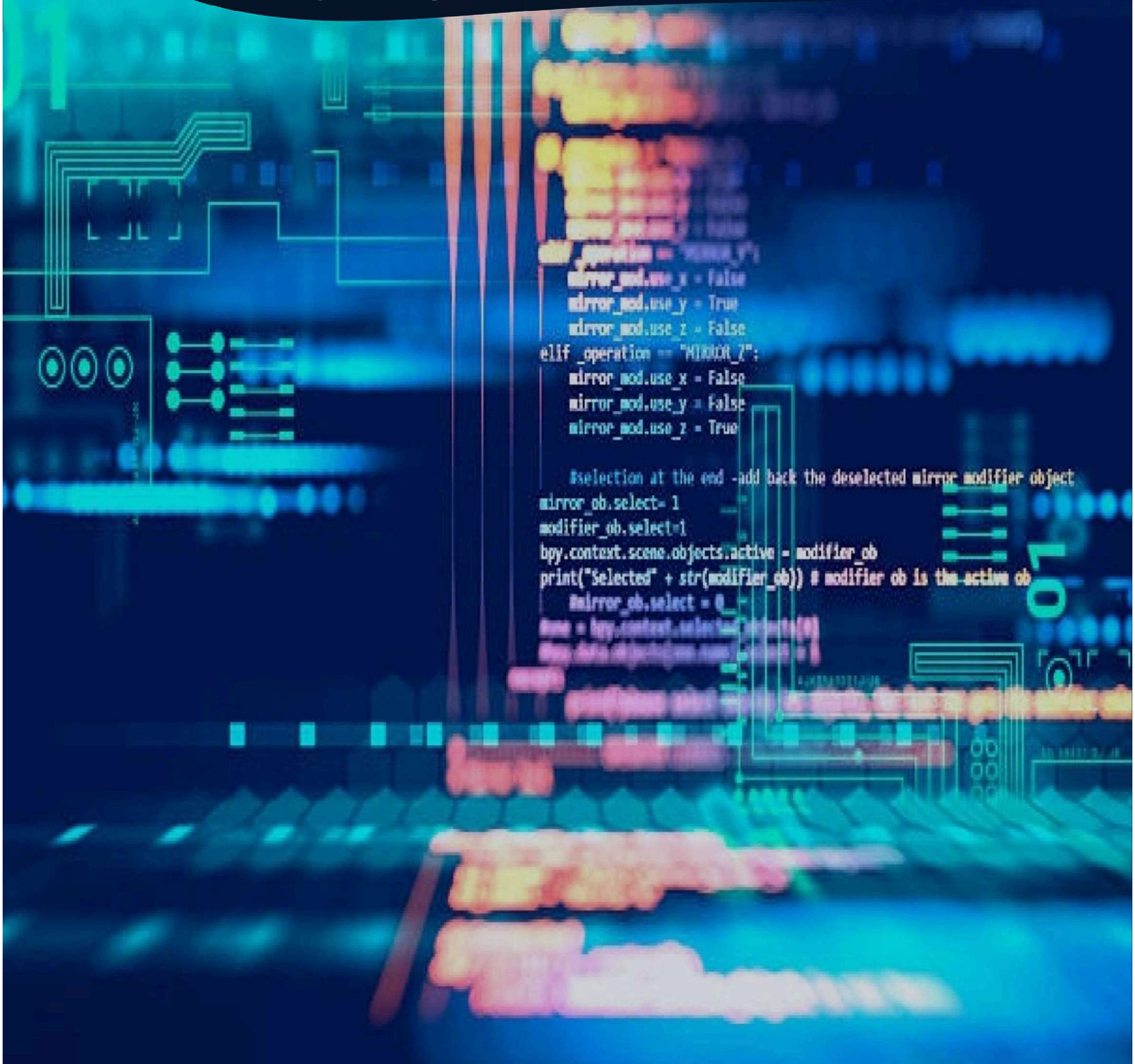

COMPILATION OF BEST RESEARCH PAPERS

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Augmenting Stock Market Prediction with CNN-LSTM Refined Model

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ABSTRACT

Achieving high accuracy in stock market prediction is crucial for effective investment strategies. Traditional methods often struggle to capture the complexities of market dynamics. This research discovers the combination of Artificial Intelligence (AI) and Machine Learning (ML) techniques, specifically Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) , to enhance predictive capabilities. Existing stock market prediction software relies on statistical models and technical analysis, which may not fully encompass market behavior. AI and ML methods offer potential to revolutionize prediction accuracy. This paper introduces the CNN-LSTM Refined Model, combining CNN layers for spatial features and LSTM layers for temporal dependencies. The model adapts to intricate patterns within stock market data. Through rigorous experimentation and real-world data evaluation, the CNN-LSTM Refined Model demonstrates promising results in accuracy and reliability. Feature engineering techniques further enhance predictive performance. By embracing AI, ML, and feature engineering, the CNN-LSTM Refined Model advances stock market prediction, providing investors and financial analysts with invaluable insights for informed decision-making in today's dynamic financial landscape.

KEYWORDS: *Stock market prediction, Convolutional Neural Networks (CNN), Long short-term Memory (LSTM), Artificial Intelligence (AI), Machine Learning (ML), Feature engineering.*

INTRODUCTION

Navigating the stock market is like finding your way through a maze. Making smart decisions can be tough because the market moves quickly and is often unpredictable. But a new tool called the CNN-LSTM Refined Model has been developed to help. It uses Artificial Intelligence and Machine Learning to predict market changes better than traditional methods.

This model combines the techniques of Convolutional Neural Networks (CNN) to identify hidden patterns existing in the data and Long Short-Term Memory (LSTM) networks to understand how those patterns change over time. It's like having a detective who sees the big picture and how things change over time. Tests using real market data show that this model works well. The model has been further tweaked to make it even better at predicting.

The CNN-LSTM Refined Model could change how investors make decisions. By using AI and ML, it could give valuable insights into the stock market's ups and downs. This could help investors make smarter choices in today's fast-moving market.

LITERATURE SURVEY

The research conducted by K. Hiba Sadia et.al delves into the application of machine learning techniques viz. random forest and support Vector Machines (SVM) in predicting stock market trends. The study reveals that random forest surpasses SVM in accuracy, providing significant guidance for potential investors. The research by Awais Mehmood et.al introduces a novel hybrid model for predicting stock closing prices. This model combines LSTM and BiLSTM architectures incorporating news sentiments and historical stock data. The model demonstrates enhanced prediction accuracy, especially for a 30-day forecast. Jinan Zou et.al. depicts the applications of deep learning techniques in predicting stock market trends. The suvery gives a better understanding of stock market trends and identifying future directions. V V Sesi Kumar's research explores the realm of stock market forecasting utilizing machine learning algorithms namely Logistic Regression, Decision Tree, SVM, Random Forest, and LSTM. Through a thorough comparison of these algorithms, it singles out SVM and LSTM as particularly promising for accurate prediction of stock prices. Sonali Antad et.al developed a Stock Price Prediction Website that utilizes the Linear Regression algorithm. The research can generate predictions for various timeframes, from the next day to the next 360 days. Troy J. Strader et.al. did a thorough examination of machine learning techniques for predicting the stock market.

PROPOSED SYSTEM

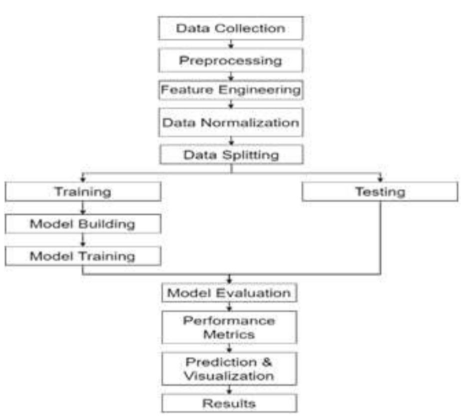

Fig. 1. LSTM-CNN Hybrid Model Proposed System

As shown in Figure 1, the system involves of the following steps:

Data Collection:Historical stock market data is taken from Yahoo Finance, including features like opening price, closing price, highs, lowsRelative Strength Index (RSI) and Exponential Moving Averages (EMA).

Data Preprocessing:The collected data is preprocessed by calculating RSI and EMA.

Feature Engineering:Correlation coefficients are calculated to identify the most influential features for predicting the next day's stock price. Data Normalization:Min-Max scaling is applied to normalize the data.

Data Splitting:The dataset is split into 80:20 ratio into training and testing data.

Model Building:A deep learning model is constructed, CNN and LSTM network. The model architecture includes multiple layers of CNN for feature extraction, followed by LSTM layers to capture sequential dependencies in the data.

As shown in Figure 2, The model integrates CNN and LSTM networks for sequence data classification. CNN layers extract features, followed by LSTM layers capturing sequential dependencies. Dropout regularization prevents overfitting, and a dense layer refines features for classification.

Model Training: The constructed model is trained to minimize the loss function. The training process comprises of updating the model parameters iteratively through several epochs to enhance predictive accuracy.

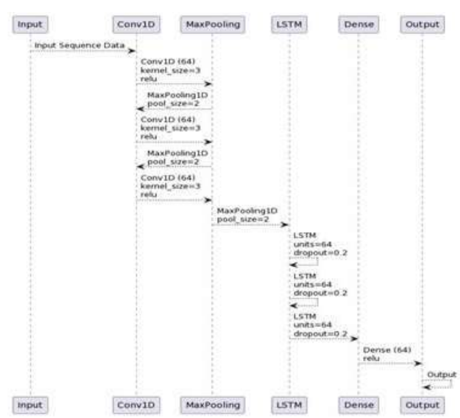

Fig. 2. LSTM-CNN Hybrid Model

Prediction and Visualization: Finally, the trained model is utilized to predict stock prices based on input features. Predicted values are compared against actual values from the testing dataset, and visualizations such as line plots are generated to illustrate the model's predictions and evaluate its performance.

LSTM Model : Long Short-Term Memory (LSTM) is a crucial component in computer programs, functioning akin to an intelligent brain cell. Illustrated in Figure 3, LSTMs possess memory cells that retain information over extended periods, akin to memory boxes. These cells are regulated by three gate types—input, output and the forget gates. The gates manage the manage information flow, determining what to retain, incorporate, or output.

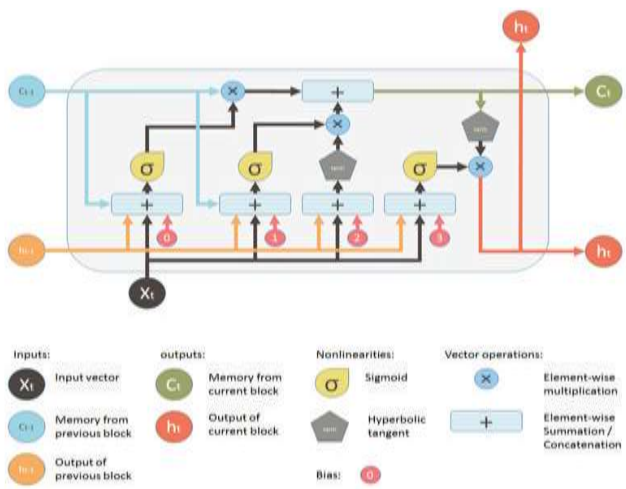

Fig. 3. LSTM Model

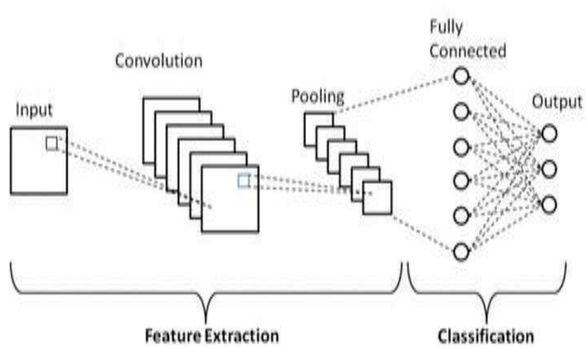

Fig. 4. CNN Model

Figure 4 shows the architecture of the Convolutional Neural Network (CNN). First, the convolutional layer takes as input the image and applies filters to detect the features like edges or textures through convolution operations. An activation function, typically ReLU, introduces non-linearity for learning complex patterns. The pooling layer reduces spatial dimensions while retaining crucial information, aiding in computational efficiency and preventing overfitting. Flattening gives a one-dimensional vector from the pooled feature maps into a one-dimensional vector. This further is taken as input to fully connected layers. These dense layers conduct intricate computations to capture high-level features. Finally, the output layer generates predictions or classifications based on learned features.

IMPLEMENTATION

Implementation includes tools that are utilized, dataset employed, and the results. The LSTM-CNN model is implemented as shown in Figure 5

Data Collection and Pre-processing

Begin by collecting historical stock price data from Yahoo Finance. This dataset should include features like opening and closing prices, volume, etc. Technical indicators like the Relative Strength Index (RSI) and Exponential Moving Averages (EMA) are calculate. This ensure the data is cleaned and preprocessed, handling missing values and adjusting the dataset to include necessary features and the target variable, which is typically the next day's closing price.

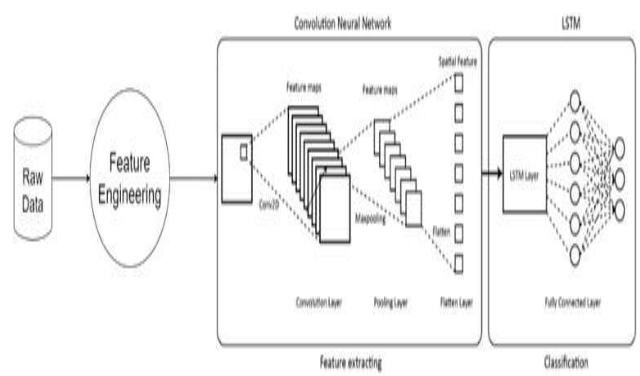

Fig. 5. LSTM-CNN Refined Model

Correlation analysis identifies the most relevant features for predicting future stock prices. Select the top k features based on their correlation as shown in Figure 6with the target variable, discarding less influential features to simplify the model and improve efficiency. Normalize the selected the model. Features were selected based on their correlation with the target variable (Next Close price). The top 7 features were retained for model training.

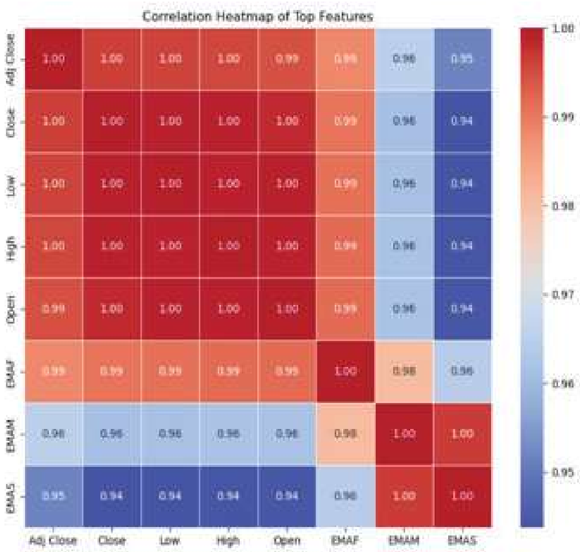

Fig. 6. Heat Map

Data Scaling: Min-Max scaling was applied to ensure all features are within the same range. This scales the range between 0 and 1.

Model Architecture: as shown in Figure 7 the model begins with a Conv1D layer with 32 filters, 5 as the kernel size, and ReLU as the activation function. This layer performs 1-dimensional convolutional operations on the input data. Subsequently, a MaxPooling1D layer with pool size 2 is added, reducing the dimensionality of the data by taking the maximum value over a sliding window of size 2. Another Conv1D layer follows, with 64 filters, , 5 as the kernel size, and ReLU as the activation unction, further extracting features from the data. Another MaxPooling1D layer is applied to reduce dimensionality. Next, three LSTM layers with 64 units each are added for sequence modeling. The dropout rate is 0.5 for each LSTM layer thus preventing overfitting. After the LSTM layers, a Dense layer with 32 units and a ReLU as the activation function is introduced. A Dense layer with 1 unit (output layer) is added finally for regression, producing a single continuous output value.

Performance Evaluation: The dataset was fragmented into two sets namely training and testing, typically using an 80-20. The model was compiled with an appropriate optimizer, loss function, and evaluation metric. With the training of the model on the training dataset for a sufficient number of epochs, the model is monitored for both training and validation loss. This ensures that the model is not overfitting.

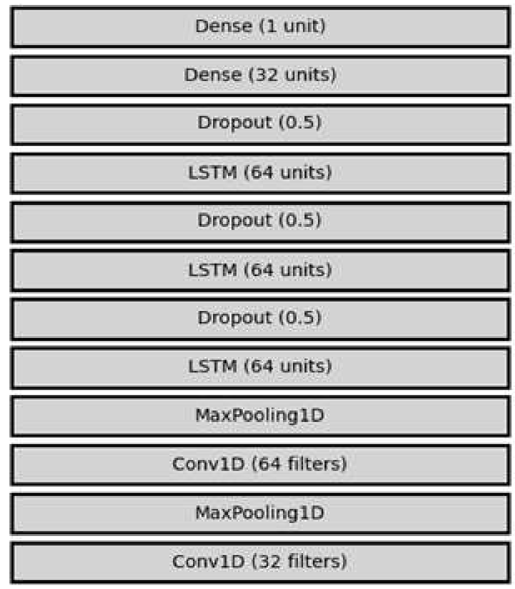

Fig. 7: Neural Network Architecture

The model is then evaluated for performance on the unseen testing dataset using metrics like Mean Squared Error (MSE) and Mean Absolute

Analyzing the predicted outputs against the actual values to assess the model's accuracy and prospective

for real-world application in stock price prediction is done for the prediction accuracy.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{actual_i - forecast_i}{actual_i}\right| X\ 100$$

RESULTS

The Mean Absolute Percentage Error (MAPE) between the predicted (y_pred) and actual (y_test)

values is calculated. MAPE is converted into accuracy and the result is 97.00464 providing an assessment of the model's predictive performance Figure 8, illustrates the model's performance, demonstrating an impressive accuracy rate of 97.00%.

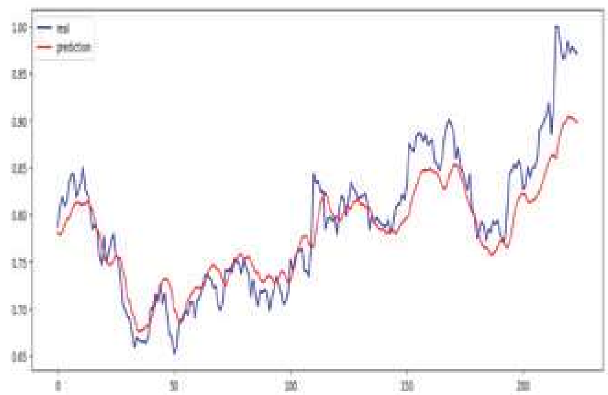

Fig. 8. Model Performance

CONCLUSION

The CNN-LSTM Refined Model, incorporating Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, offers a promising approach for stock market prediction. Through the integration of AI and ML techniques, the model demonstrates improved accuracy compared to traditional methods. Continued research and refinement hold the potential to provide valuable insights for investors in navigating the dynamic financial landscape.

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AI-Based Learning for Olympic Game: Football

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ABSTRACT

Today we live in the 20th century and sports play a significant role not only in the form of entertainment but also as a platform for social, cultural, and economic activities. The world has been entirely crafted by modern technologies. Nowadays we also have various types of Academies for all kinds of sports that help us get trained from basic to advanced, but somehow today there are still some parts of the world where modern technologies and their advantages have not been introduced. Not everyone can afford the fancy training academies to learn a specific sport.

The rural part of the world is still unaware of how the world has adapted modern means of learning games through newly designed technologies. Even though every person carries a smartphone in today's date making the right use of it is still not known for many people. In many educational settings, students face a lack of engagement, limited accessibility to quality resources, and an approach that fails to address individual learning styles and preferences. Many times even after having any sport as a hobby, people tend to give up just because they can't afford to learn it through any academy.

KEYWORDS: *AIML, Artificial intelligence,Machine learning, Predictive analysis, Posture detection, Generative AI.*

INTRODUCTION

Have you ever wondered what if technology started ruling the world?? We can only wonder about things like flying cars, robots walking on streets, doctors on mobile phones, and whatnot!! Today the world is on its way to get as digitalised as possible. People are busy finding shortcuts for all of the tedious work. The world has already experienced how things can be managed digitally without human hands during the COVID-19 period. And this thing has brought an immense change in the world. People have started depending on technology more than on themselves and this has led to the invention of AI i.e. Artificial Intelligence.

Artificial means man-made and intelligence means the ability to think which makes AI a man-made ability to think. AI is nothing but a tool created by a man that can think like a human brain. AI is also defined as the field of computer science where a tool can think like a human brain, work like a human brain, solve problems like the human brain, and make decisions like a human brain. Many people consider AI as the latest technology but this technology has existed for ages. The first AI work was done by Warren McCulloch and Walter Pits in 1943 and was known as a model named Artificial Neurons. The latest AI technologies that have been set as a new trend are the Chat-Bots. Chatbot is very similar to a program that processes human conversation and allows a human to chat with the device as if they are communicating with another human only. It helps in every sector of a human being's daily life. This is one of the best technology that has been invented by a human himself.

Artificial Intelligence has set a new and the highest record in the world. People have started depending on AI tools for every aspect of their life. AI is set on Machine Learning and Deep Learning algorithms. AI has two types Weak AI and Strong AI.

Weak AI:- Also known as ANI(Artificial Narrow Intelligence) is designed to perform specific tasks, this is the most popularly used AI in our day-to-day life such as Apple's Siri, Amazon's Alexa, etc.

Strong AI:- Also known as Artificial Strong Intelligence. It is a theoretical part of AI where machines have intelligence equal to the human brain. Since this is the theoretical part there are no real-world examples related to Strong AI but the research is still going on and one example we can take for ASI is science fiction such as HAL etc.

AI IN SPORTS

Since AI is on its way to making a remarkable journey in every field, one such field where AI is needed is the Sports field. There are lot many things in this field where some things cannot be managed manually or can be managed manually but making use of AI tools can make the entire thing very easy and lightweight. People have already started using such tools in games for eg National Football League is using AI tools for analyzing game films and managing the performance of each player. Since the use of artificial intelligence in the sports industry is kind of still in its early stage innovations are still to be taken place.

AI IN FOOTBALL

Football is a team sport played between two teams which includes 11 players in each team. The objective of this sport is that the team needs to score a goal by getting the ball into the opponent team's net. The team that scores the maximum goals within the allotted time wins the match. Football is played worldwide but it is not that popular among some of the rural parts due to a lack of proper infrastructure and expert training, still, the passion to play football remains the same among individuals. Such problems can be solved by introducing AI (Artificial Intelligence) in football. As we live in the 21st century we can expect a mobile phone in every corner of the world. So developing an AI-based application that not only helps in learning the game but also keeps track of what kind of workout is needed, how the base for the football player can be built, the nutrition needed for a player, etc can all be stated under one application. This will not only help players to learn the sport but also help in knowing all the basic and important requirements that are needed to play the game. To become a football player fitness and workout plays an important role.

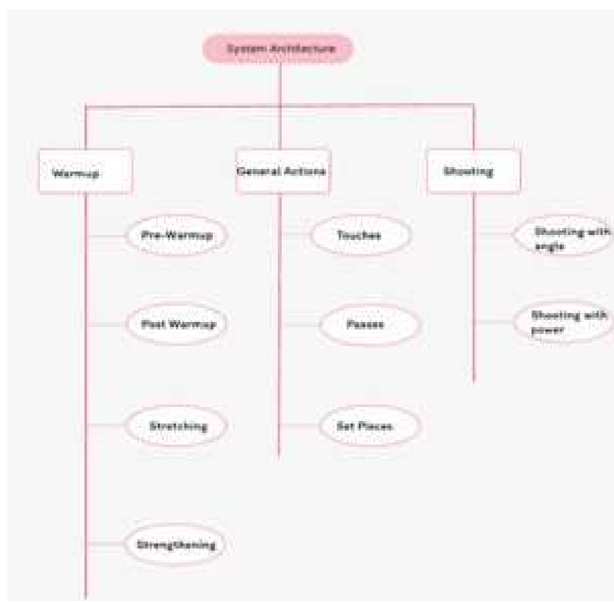
SYSTEM ARCHITECTURE

Now, the application can be built by considering 3 major categories

1) Warmup

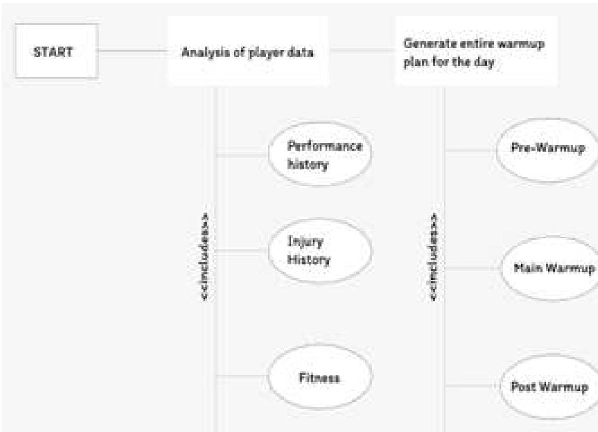
2) General Actions

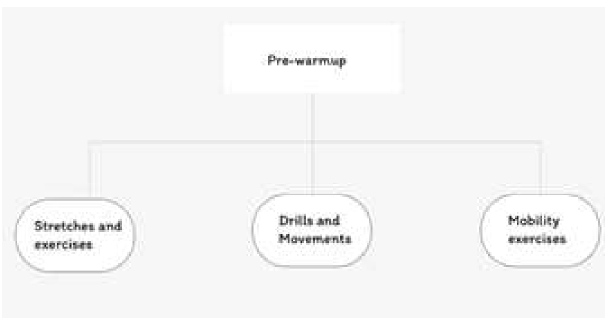
3) Shooting

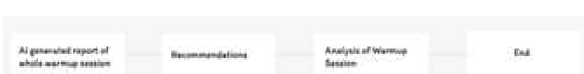


1) Warmup:- Warmup in Football plays a crucial role for any football player to build a proper physic and strengthen themselves for better gameplay. Warmup includes four subcategories Pre Warmup, Post warmup, Stretching, and Strengthening.

General View of how exactly the AI can help with the warmup







As we have seen in the above diagrams the entire warm-up session for football includes lots many steps and doing each of them manually can lead to huge mistakes, but what if there is an application that can control every step depending on the player's health? For this purpose we can consider the algorithm above, which is;Once the application is opened the very first thing to notice must be the player's record which will include his/her injury history, performance history, fitness, etc. Next comes the entire Warm-up plan for the day and this plan will be completely AI-generated depending upon the player's fitness. Now this plan will be divided into three sections which will be Pre-Warmup, Main-Warm-up, and Post-Warmup.

Pre-warmup must be done before the main warmup. This helps the players to prepare themselves for the game and it acts as a preparatory step that will gradually help with heart rate, blood flow, etc. Pre-Warmup is then divided into three parts which are Stretches and Exercises, Drills and Movements, and Mobility Exercises. Now these Pre-Warmup exercises will be entirely generated by Artificial Intelligence starting from types of stretches to how many exercises everything will be under the AI control again by considering the player's record.

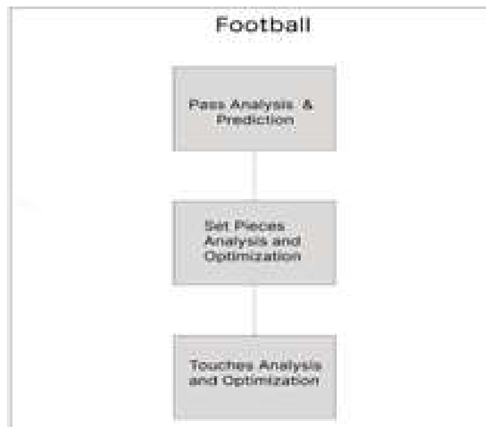
Main Warm-up is the crucial step for a football player as this warmup routine includes the actual practice before the match begins. This routine is divided into three parts i.e. Aerobic Exercises, Stretching, and Football Drills. The Aerobic Exercises consist of three main exercises which are Running, Shuttle run, and sprints. The AI can take control of all the aerobics needed for the player that are important for a football match. The next part will be the Stretching, now the stretching part depends from person to person in what angle a player should stretch himself/herself. The stretching angles are very important to consider, and doing this manually without any proper guidance can lead to wrong posture. Then next comes the Drills. The drills are completely coach-designed exercises that every player has to exercise before the match. The drills include passing and dribbling. The passing drill includes players passing the ball among each other in variety of patterns that emphasize accuracy, time, and technique. These parameters can be measured by AI so that each player understands his/her potential. The next exercise in the drill section is the dribbling. The dribbling includes cone dribbling exercises where players learn to navigate through the defenders. So these are some main warmup exercises that can controlled by AI.

The next are the Post Warmup exercises. These exercises are been done after the football match. This warmup also plays an important role after the match as the player needs to relax. This warmup is done for the relaxation of the muscles. Majorly the post-warmup includes three main categories which are Cool-down exercises, Analysis of recovery, and Nutrition check. The cool-down exercises have the subcategories Light jogging, stretch, and Rehydration. Then next comes the Analysis of recovery which is very important to be measured. This analysis includes the heart rate, pulse rate, blood pressure, and muscle fatigue. These parameters are necessary to be calculated for each player as it plays a very important role in the physical health of a player. The smartphone's camera and flash can be used to capture the PPG (photoplethysmography) signals from a user's fingertip or face, enabling them to measure this parameter. The next and last but very important category is Nutrition Check. This includes protein intake, a balanced diet, and physio exercises. All of these can be measured based on parameters that were calculated in the analysis of recovery. The basic physio exercises that are needed for a player after the game can be given with the help of AI.

Now a complete report of the whole warmup session can be generated by AI so that a player knows his/her routine. The recommendation can also be suggested by AI based on the generated report and lastly, the player can easily analyze the warmup session. This completes the warmup part for the football game.

2) General Actions:- The General Actions are the actions that are involved during playing football. These actions include Touches, Passes, and Set Pieces.

1) Pass Analysis and Prediction:- This segment includes the analysis and prediction of pass patterns. Passes are very crucial in football as it improves the player's strategy and team coordination needed for the game. The Pass Analysis can include Pass Accuracy(how accurate the pass is), Pass Length(length of the pass), Pass Direction(angle of the pass), and Pass Position(the position of both passer and receiver) These are some of the parameters that can be analyzed with the help of AI. By considering these factors AI can help the player to understand the correct position needed for the Passes. The next is the Pass Prediction. Building upon the insights gained from pass analysis, this AI module predicts potential pass options for players in real-time situations. It looks at how and where the players are positioned and also considers the passing history of individual players and teams as a whole. Using this information, the AI predicts possible passing options for a player in possession of the ball.



2) Set pieces analysis and optimization:- AI algorithms identify patterns and trends in set piece execution and outcomes. For example, they may recognize that a certain player is particularly effective at delivering corner kicks to a specific area in the penalty box, or that the opposing team tends to use a particular defensive formation during free kicks. Based on the analysis of past data and patterns, AI algorithms suggest optimization strategies for set pieces. This could involve recommending specific tactics, player positioning, and delivery techniques to increase the likelihood of scoring from set pieces.

3) Touches analysis and optimization:- AI analyzes the collected data to assess individual player performance in terms of touches. It evaluates factors such as passing accuracy, dribbling success rate, effectiveness in maintaining possession, and contribution to scoring opportunities. By identifying strengths and weaknesses in players' touch patterns, AI helps coaches tailor training programs and tactical strategies to improve overall team performance. Based on the analysis of touch data and tactical insights, AI suggests optimization strategies to

enhance player touches and team performance. This may involve recommendations for improving passing accuracy, increasing ball retention, or creating scoring opportunities through effective ball circulation and movement. For example, AI might suggest specific training drills to improve players' first touch

.

3) Shooting:- In football, "shooting" refers to the action of a player attempting to score a goal by kicking the ball towards the opponent's goal. Shooting is the most fundamental skill in football that requires proper technique and power. Shooting can be done from various angles depending on the player’s skills. So mainly shooting can be divided into two parts

1) Shooting with angle:- AI can analyze vast amounts of data of players playing history which can include players’ positions, shooting angles, etc. By identifying the trends and patterns in the data the AI can provide the most effective strategy for shooting. The shooting angle plays a very important role in this sport, The ball needs to be kicked at proper angle in the goalpost. So AI can assist with the proper angle to a player. AI can analyze to player’s history on previous strategies and angles used by a player and can help by suggesting better angles. This can help with the player’s improvement with the angles.

2) Shooting with Power:- AI can analyze the biomechanics of players' shooting techniques to identify optimal methods for generating power. This analysis can include factors such as the angle of approach, the position of the body, and the speed of the kicking motion. By analyzing data on players' physical attributes and performance metrics, AI can recommend exercises and training regimes tailored to enhancing explosive strength and kicking power. By considering factors such as distance from the goal, angle of approach, and goalkeeper positioning, AI can recommend the optimal amount of power needed for successful shooting.

ROLE OF GENERATIVE-AI

Generative AI refers to a class of artificial intelligence techniques and algorithms that are designed to create or generate new content, often in the form of images, text, audio, or even video, that is similar to examples it has been trained on. Generative-AI can play a major role in this application by analyzing the large datasets of the players and provide insights into players' potential based on their playing style, statistics, and other factors. It can also play a role of virtual coach for the individual training. The application can generate personalized training content tailored to individual users' skill levels, positions, and learning preferences. For example, it could create custom drills, exercises, or tactical challenges based on the user's strengths and weaknesses. It can also generate the entire report for a player. By integrating generative AI into a football learning application, users can benefit from personalized, interactive, and immersive learning experiences that enhance their skills, knowledge, and understanding of the game.

BENEFITS

- Personalised Training:- This AI-based application can help with individual training to a player by analyzing payer’s data, strengths, weaknesses, etc
- Skill Development: The player can improve his/her skills as this application can make a player learn from the utmost basic things like dribbling, passing, drills, etc.
- Accessible Learning:- This application can be accessible anytime anywhere, which will allow users to learn at their own pace through their smartphones.
- Balancing Health:- This application not only aims to provide learning skills but also provides tips on maintaining proper health by providing a balanced diet physio exercises etc
- Posture Detection:- The correct posture needed for this sport can also be stated by this application.
- Real-time Feedback:- At the end of every session every-day this application generates an entire report for the player in the form of feedback.

LIMITATIONS

Developing AI algorithms that accurately analyze complex football scenarios and provide meaningful feedback requires advanced technical expertise and computational resources. It is not possible that a player can completely become a full-fledged football player by learning through this application. While AI can offer valuable insights and recommendations, it cannot fully replace human expertise, particularly in subjective areas such as coaching, strategy, and player development. One cannot rely on AI learning applications, over-relying can lead to a player's lack of thinking power, the potential to think in real-time difficulties, etc. It is kind of difficult to cover all the player's requirements under one application. Addressing these limitations requires a multidisciplinary approach that combines technical innovation with ethical, and practical considerations to create AI-based football learning applications that are inclusive, effective, and ethically responsible.

CONCLUSION

In conclusion, AI-based football learning applications represent a promising avenue for enhancing player development, coaching methodologies, and personalized training in the sport. This application can prove a boon for society especially the rural parts who can't afford training academies. One can learn all the basic things required for this sport. Although considering the limits that human expertise is needed for learning anything in this world, this application can at least provide basic knowledge to a player who is willing to learn this sport at their level. This AI-based football learning application has the potential to revolutionize the way players learn, train, and engage with the sport, ultimately contributing to the growth and enjoyment of football worldwide.

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Machine Learning Multi-Classifier Approach for Proactive Cyber Defence

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ABSTRACT

In today's digital landscape, the growing complexity and frequency of cyber-attacks pose serious threats to the security and integrity of networks, systems, and sensitive information. Conventional cyber-threat detection techniques, which largely rely on signature-based mechanisms, often fail to recognize new or evolving attack patterns, leaving organisations exposed to potential security breaches. To overcome these limitations, this project presents a machine learning–based cyber-attack detection approach that leverages network traffic analysis. The proposed system employs Random Forest, XGBoost, and LightGBM algorithms to classify network behaviour as either normal or malicious based on traffic characteristics. By capturing and analysing relationships among multiple network features, the system is designed to detect cyber threats in real time, thereby enhancing both the accuracy and efficiency of security monitoring. To address the challenge of limited availability of standardized network datasets, this study utilises the UNSW-NB15 dataset, which combines realistic normal network traffic with synthetically generated modern attack scenarios. Furthermore, Decision Trees and Confusion Matrices are used to evaluate model performance, enabling the assessment of detection accuracy and reduction of false positive rates. Experimental results demonstrate that ensemble machine learning techniques are highly effective in identifying diverse cyber-attack types, significantly strengthening the protection of digital infrastructures.

KEYWORDS: UNSW-NB15, Decision Trees, Random Forest, machine learning, Attack Detection, Cybersecurity

INTRODUCTION

The continuous growth of digital technologies has significantly increased exposure to cyber threats, creating serious risks for the confidentiality, availability, and reliability of computer networks and information systems. As digital infrastructures become more complex, ensuring cybersecurity has become a fundamental requirement for protecting sensitive data and maintaining operational continuity. To effectively counter modern cyber threats, there is a strong need for intelligent and proactive detection mechanisms capable of identifying attacks at an early stage.

This study emphasizes the application of machine learning techniques to strengthen cyber-attack detection capabilities. By examining network traffic patterns, the proposed approach enables real-time identification of suspicious activities within a network environment. The integration of Random Forest, XGBoost, and LightGBM algorithms allows the system to learn complex attack behaviors and rapidly differentiate between legitimate and malicious traffic, leading to faster incident response and enhanced security enforcement.

Cybersecurity focuses on defending digital systems and communication networks from a wide range of malicious activities, including Distributed Denial of Service (DDoS) attacks, malware intrusions, fuzzing attempts, and worm-based exploits. Traditional security solutions often rely on static rules or signature-based detection, which limits their ability to adapt to newly emerging or modified attack strategies. In contrast, machine learning–driven solutions can autonomously analyse large-scale network data, uncover hidden patterns, and detect anomalies that indicate potential cyber threats. To address these challenges, this research proposes an intelligent cyber-attack detection system based on ensemble learning methods, specifically Random Forest, XGBoost, and LightGBM. The system analyses network traffic attributes to accurately classify activities as either benign or malicious. The UNSW-NB15 dataset is utilised in this study, as it combines authentic normal network behaviour with synthetically generated modern attack scenarios, making it well-suited for evaluating intrusion detection models.

RELATED WORK/ LITERATURE REVIEW

The rapid growth of networked systems and digital services has led to a corresponding increase in the frequency and sophistication of cyber-attacks. Traditional intrusion detection systems (IDS), which are largely based on rule-based or signature-based mechanisms, have been widely used to detect known attack patterns. However, these approaches suffer from significant limitations, particularly in identifying zero-day attacks and adapting to evolving threat landscapes [1]. As a result, researchers have increasingly focused on intelligent and adaptive detection techniques to enhance cybersecurity defences.

Machine learning (ML) has emerged as a powerful tool for cyber-attack detection due to its ability to learn complex patterns from large volumes of network traffic data. Several studies have demonstrated that ML-based IDS can outperform conventional methods by identifying anomalous behaviors and previously unseen attack types [2]. Supervised learning algorithms such as Decision Trees, Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN) have been extensively explored for network intrusion detection, showing promising results in terms of detection accuracy and adaptability [3].

Among these techniques, ensemble learning methods have gained particular attention due to their robustness and high predictive performance. Random Forest, an ensemble of decision trees, has been widely applied in intrusion detection systems because of its ability to handle high-dimensional data, reduce overfitting, and maintain strong generalization performance [4]. Studies have shown that Random Forest-based IDS achieve high detection rates across multiple attack categories while maintaining low false positive rates [5].

Gradient boosting algorithms, such as XGBoost and LightGBM, have further advanced the performance of cyber-attack detection systems. XGBoost enhances traditional gradient boosting by incorporating regularization techniques and parallel processing, resulting in improved accuracy and computational efficiency [6]. Research indicates that XGBoost performs exceptionally well in detecting complex attack patterns, particularly in large-scale and imbalanced network datasets [7]. Similarly, LightGBM has been recognized for its speed and scalability, making it suitable for real-time intrusion detection scenarios [8]. Its leaf-wise tree growth strategy allows it to capture intricate feature interactions while reducing training time.

The choice of dataset plays a critical role in evaluating the effectiveness of intrusion detection models. Earlier datasets such as KDD Cup 99 and NSL-KDD have been widely used; however, they are often criticized for redundancy and lack of representation of modern attack behaviors [9]. To address these shortcomings, the UNSW-NB15 dataset was introduced, incorporating real-world normal traffic along with contemporary synthetic attack scenarios [10]. Several studies have validated the suitability of UNSW-NB15 for benchmarking ML-based IDS due to its diverse feature set and realistic attack distribution.

Recent research has emphasized hybrid and ensemble-based detection frameworks that combine multiple machine learning algorithms to improve detection accuracy and reduce false alarms [11]. By leveraging the strengths of different classifiers, such systems can better capture complex relationships among network features and enhance overall system reliability. Performance evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrices are commonly employed to assess IDS effectiveness and ensure balanced detection across attack classes [12].

In summary, existing literature highlights the effectiveness of ensemble machine learning techniques in cyber-attack detection. While Random Forest, XGBoost, and LightGBM have individually demonstrated strong performance, integrating these models offers a promising direction for developing high-accuracy, real-time intrusion detection systems capable of addressing modern cybersecurity challenges.

REVIEW OF THE UNSW-NB15 DATASET

The UNSW-NB15 dataset is a modern benchmark dataset generated using the IXIA PerfectStorm tool, combining real-world normal traffic with contemporary attack scenarios. It includes nine attack categories and 49 network features, making it suitable for evaluating machine learning–based intrusion detection models.

Data Collection Process

The dataset was collected in a controlled real-world testbed environment using the IXIA PerfectStorm traffic generation tool. Both legitimate and malicious network traffic were generated to reflect realistic operating conditions. Normal traffic emulated common network activities such as web browsing, email exchange, file transfers, and database access, while malicious traffic consisted of nine distinct attack categories representing both modern and traditional attack techniques. Captured network packets were processed using feature extraction tools to derive 49 relevant network attributes from the raw traffic data. The resulting dataset models contemporary cyber-attack scenarios, ensuring the applicability of trained machine learning models to current cybersecurity threats.

Data Volume and Composition

The dataset contains more than 2.5 million records. It includes both normal and attack traffic, making it well-suited for binary and multiclass classification tasks [13].

METHODOLOGY

Prior to model training, the raw network traffic data undergoes a preprocessing phase to improve data quality and model performance Figure 1. Show system flow. This stage focuses on eliminating noise and irrelevant information from the dataset. Records with zero connection duration and undefined connection states are removed to prevent misleading patterns. In addition, feature scaling is applied to normalize the input attributes, ensuring uniform contribution of features during model training.

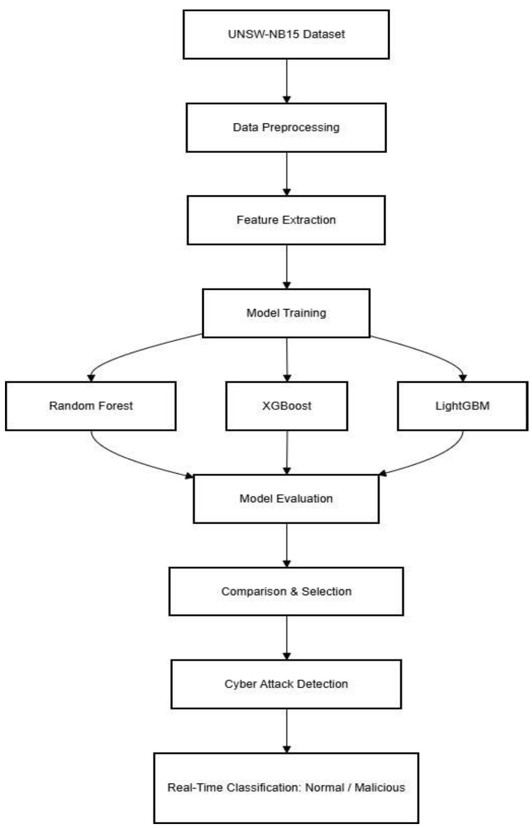

Figure 1: System flow

Random Forest–Based Attack Classification

Random Forest is an ensemble-based machine learning algorithm that constructs multiple decision trees during the training process and combines their outputs to generate final predictions. This approach enhances model stability and reduces the risk of overfitting, especially when dealing with complex, noisy, or class-imbalanced network traffic data. In the proposed system, the Random Forest model demonstrates strong performance in attack classification, achieving an accuracy of approximately 98.09%. The evaluation results of the model are presented in the corresponding performance analysis section.the Figure 2.

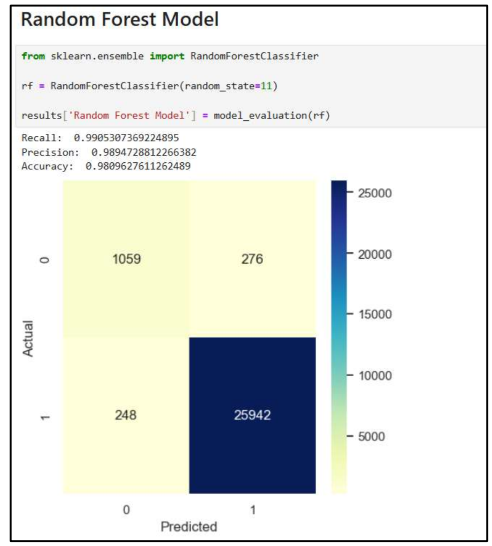

Figure 2: Random Forest Model Evaluation

Feature Ranking from Random Forest:

XGBoost Model for Categorization

XGBoost, or Extreme Gradient Boosting, is a powerful ensemble learning technique that constructs decision trees in a sequential manner, where each new tree corrects the errors of the previous ones. The algorithm integrates regularization mechanisms to control model complexity and reduce overfitting. Due to its optimized implementation, including parallel processing and efficient handling of sparse data, XGBoost is particularly effective for large-scale datasets. In this study, the XGBoost model achieves an attack classification accuracy of approximately 98.05%, with performance evaluation results illustrated in the corresponding analysis section figure 3.

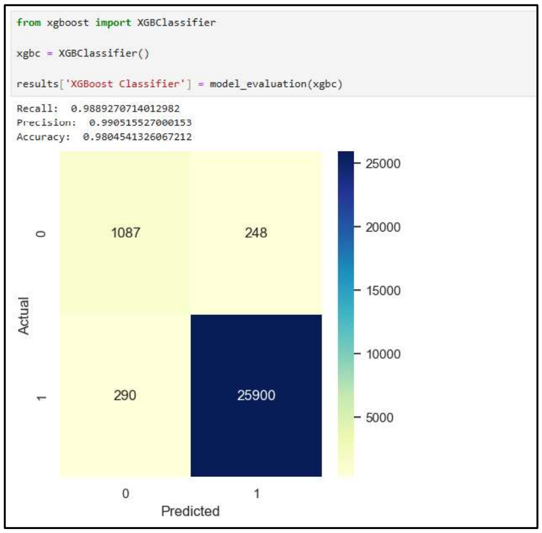

Figure 3: XGBoost Model Evaluation

LightGBM Model for Categorization

Light Gradient Boosting Machine (LightGBM) is designed for high computational efficiency and low memory consumption. It utilises histogram-based learning techniques along with a leaf-wise tree growth strategy, enabling faster training and effective handling of large and high-dimensional datasets. In the proposed system, the LightGBM model demonstrates strong performance in attack classification, achieving an accuracy of approximately 98.02%. The detailed evaluation results are presented in Fig. 4.

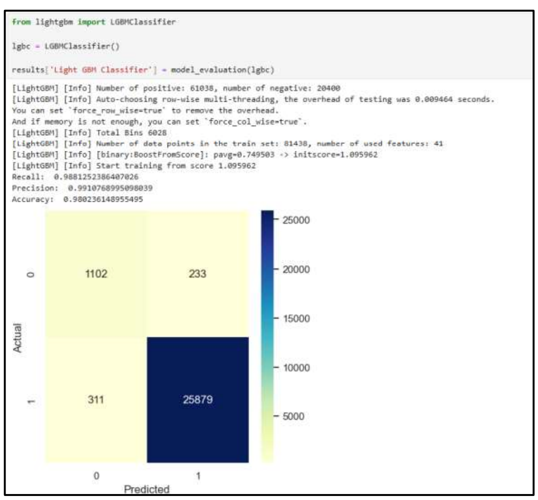

Figure 4: LightGBM Model Evaluation

RESULTS

To evaluate the performance of our model, we utilize the confusion matrix, which allows us to identify true positives, true negatives, false positives and false negatives. A confusion matrix is a technique used to estimate the performance of a classification model, specifically by showing how well the model's predictions match the actual outcomes.

The comparative evaluation of Random Forest, XGBoost, and LightGBM for attack categorization using the UNSW-NB15 dataset is given in Figure 1, it highlights the strengths of each model across key metrics: Recall, Precision, and Accuracy.

The superior recall performance of the Random Forest classifier demonstrates its effectiveness in detecting a higher proportion of malicious activities, making it suitable for intrusion detection scenarios where false-negative reduction is critical.

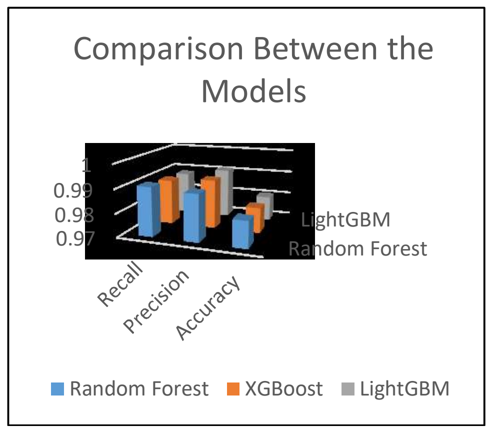

Figure 5: Model Comparison

LightGBM achieved the highest precision, highlighting its effectiveness in minimizing false positives, which is crucial for automated response systems sensitive to false alarms. Overall accuracy was similar across all models, with Random Forest and XGBoost performing slightly better than LightGBM. The choice of model should therefore depend on system objectives: Random Forest is ideal for maximizing attack detection (high recall), LightGBM is suited for applications requiring precise classification (high precision), and XGBoost provides a balanced trade-off, making it suitable for general-purpose intrusion detection. These findings emphasize the importance of selecting models based on the specific needs of network security applications.

CONCLUSION

Among the evaluated models, Random Forest, XGBoost, and LightGBM all demonstrated strong performance in cyber-attack classification, with overall accuracies close to 98%. Random Forest achieved the highest recall, indicating its superior ability to detect the majority of attack instances, making it particularly suitable for systems where minimizing false negatives is critical. LightGBM, on the other hand, achieved the highest precision, reflecting its effectiveness in reducing false positives, which is essential for automated response systems that may be disrupted by frequent false alarms. XGBoost provided a balanced performance across both metrics, offering a trade-off between recall and precision and making it a versatile option for general-purpose intrusion detection. These results suggest that the optimal model choice depends on the specific objectives of the detection system: Random Forest for comprehensive attack coverage, LightGBM for precise classification, and XGBoost for balanced performance. Overall, the findings highlight the importance of tailoring model selection to the operational requirements and priorities of network security applications.

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MoodFlix: A Sentiment-Based Movie and Song Recommendation System

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***Abstract*—MoodFlix is an intelligent recommendation system designed to enhance user experience by providing personal- ized movie and song suggestions based on real-time sentiment analysis.The system uses CNN for face detection and KNN to classify emotions, turning facial expressions into mood-driven suggestions. The hybrid approach significantly improves accu- racy, with CNN ensuring precise facial recognition while KNN effectively classifies emotions. This research examines the design, implementation and assessment of MoodFlix, highlighting its effectiveness in sentiment-driven content recommendations.**

***Index Terms*—CNN(Convolutional Neural Networks), KNN(K- Nearest Neighbors), Sentiment Analysis, Recommendation Sys- tem, FER(Facial Expression Recognition)**

I. INTRODUCTION

Recommendation systems are key to customizing user ex- periences on digital platforms. Traditional recommendation models rely on collaborative or content-based filtering, which often lacks real-time adaptability. MoodFlix takes a novel

approach by integrating facial expression recognition into the recommendation process, ensuring suggestions align with the user's current emotional state[1,2]. The system leverages ML(Machine Learning) and DL(Deep Learning) techniques, combining it with CNN to give robust face detection and KNN for efficient emotion classification [3,4]. This paper discusses the architecture, methodology, and performance analysis of MoodFlix, highlighting its potential for enhancing user en- gagement.

This research explores various aspects of machine learning, computer vision, and user experience to improve recommen- dation accuracy. The specific areas covered include:

The system is designed primarily for movie and song recommendations, but its methodology can be extended to other forms of media, such as podcasts and audiobooks [5].The hybrid model integrating CNN and KNN achieves remarkable accuracy improvements, with face detection in- creasing from 75% to 92% and emotion recognition accuracy improving from 70% to 85% [6]. Despite a slight increase in processing time (from 50ms to 75ms per image), the enhanced precision, recall, and reduced false detections justify this trade-off[7]. The system can be integrated with existing streaming platforms, making it a valuable addition to services like Netflix, Spotify, and YouTube.

The specific objectives of this research are to enhance user experience by providing personalized movie and song recommendations based on real-time sentiment analysis. To achieve this, the system integrates facial expression recog- nition with a hybrid machine learning approach, combining CNN for face detection and KNN for emotion classification, to develop an intelligent recommendation system that adapts to user emotions, ensuring a more engaging and immersive entertainment experience, to enhance the accuracy of facial expression detection and sentiment analysis by leveraging CNN for face recognition and KNN for emotion classification. Also to ensure efficient and responsive emotion detection that works under varying environmental conditions, making the system robust and adaptable, to compare how accurate and efficient different machine learning models are for sentiment- based recommendations, specifically measuring improvements in face detection, emotion classification, precision, recall, and false detection rates, to design an intuitive and accessible interface that seamlessly integrates sentiment analysis into entertainment recommendations.

II. LITERATURE REVIEW

Facial expression-based emotion recognition has been a focal area in computer vision research for decades. Early algorithms, such as the Viola-Jones framework introduced in 2001, provided a foundation for face detection but were limited by environmental factors like lighting and background varia- tions [6]. The advent of CNN(Convolutional Neural Networks) modernized the field by providing hierarchical feature extrac- tion, mimicking the human visual system [1]. Researchersshowcased the capabilities of deep learning architectures in handling image processing tasks.

On the other hand, KNN, though a simpler algorithm, remains effective for small datasets due to its straightforward implementation and interpretability [5]. Recent studies have shown that hybrid models, combining CNN for feature ex- traction with KNN for classification, significantly improve performance [4,8]. These approaches are particularly well- suited for real-time applications, where speed and accuracy are equally important [8]. Figure 2 highlights working of K Nearest Neighbors.

III. Research Methodology

A. Data Collection

The MoodFlix system relies on high-quality datasets to train and evaluate its models.The main dataset utilized is FER-2013, which contains 35,887 images labeled with basic emotions including surprise, neutral, happiness, fear, anger, making it a vital resource.[3],[10]. To enhance the model's performance and flexibility, the images were preprocessed through steps like resizing, augmentation and normalization.[3],[10]. These steps ensured that the system could handle diverse input conditions and improve its accuracy in recognizing emotions.

B. Face Detection with CNN

The Moodflix, the face detection process employs a pre- trained CNN model, such as VGG16 or ResNet, which has been fine-tuned to suit the specific requirements of the ap- plication.[12], [13]. At the initial stage, the CNN captures essential features like textures and edges from the input image, forming a detailed representation.[12] These features are then passed through pooling layers, which reduce the feature map's dimensions while preserving critical details [12]. Finally, the fully connected layers classify the regions of the image to determine whether they contain a face [12]. This process generates bounding boxes that pinpoint the locations of detected faces, which are then forwarded to the next stage for emotion recognition.[12],[13].

C. Emotion Recognition with KNN

Following face detection, the system extracts key facial landmarks such as the eyebrows, eyes and mouth which are essential for precise evaluation of the user's emotional state [5]. The extracted features are then compared to the training dataset using KNN [5]. The algorithm determines the k-nearest neighbors which calculates Euclidean distance between the test sample and training data, facilitating the identification of the most similar data points in the feature space[5], [8]. The ma- jority emotion class among these neighbors is assigned as the user's emotion label [5], [8]. This process ensures accurate and efficient emotion classification, making the system responsive to user inputs.

Implementation Details

A. Dataset

The development and evaluation of the MoodFlix system are grounded in the FER-2013 dataset, a widely acknowledged benchmark in the domain of facial expression recognition. This dataset is particularly suitable for training machine learning models to classify emotions using facial images under varied conditions [3], [10], [13]. The dataset consists of 35,887 grayscale facial images, each with a dimensions of 48x48 pixels. Each image is annotated with one of seven emotional categories, including fear, disgust, sadness, surprise, neutrality and anger. Each of these images are stored as a string of pixel values and accompanied by an emotion label. These labels enable supervised learning, where models learn to classify images based on the visual characteristics of different expressions [3], [13]. The dataset was procured from Kaggle. The total number of images are 35,887 distributed across the 7 emotions with the distribution as shown in the Table 1.

TABLE I: Distribution of Images by Emotion

Emotion	Number of Images
Fear	5121
Surprise	4002
Disgust	547
Neutral	6198
Happy	8989
Sad	6077
Angry	4953

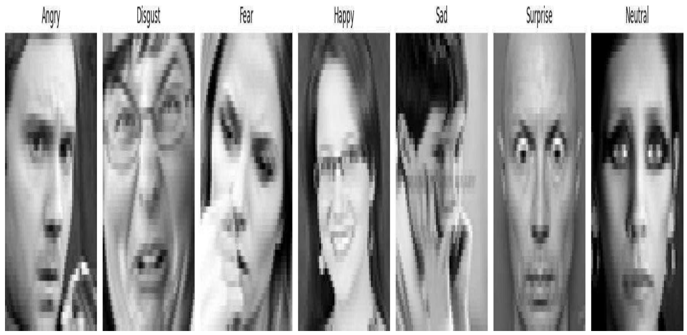

Fig. 1: Various Emotions

Figure 1 shows visual examples of each emotion type from the dataset.The dataset was divided in an 80:20 ratio, with 28,709 images (80%) allocated for training and the remaining 7,178 images (20%) for testing. This distribution ensures that the model is trained and validated on a well-balanced mix of expressions, increasing its generalizability and robustness.[10],[13]

B. *Convolutional Neural Networks*

CNN is vital for precise face detection in MoodFlix, pro- cessing images through multiple layers. Convolutional layers extract features like edges and textures, while activation func- tions introduce non-linearity for pattern recognition. Pooling layers refine feature maps by reducing dimensions and preserv- ing key details. Fully connected layers then classify detected regions as faces. Pre-trained on datasets like VGGFace or ResNet, the CNN model ensures reliable detection even in challenging conditions like poor lighting and occlusions.

C. *Architecture of CNN*

The process begins with the input layer, where the users's face is captured through a live camera. The image is then pre-processed, converted into a suitable format(grayscale or RGB), and resized to a fixed dimension to maintain consistency in the model's input.

Once the image is prepared, it passes through multiple convolutional layers, where CNN applies filters to extract meaningful facial features. The first convolutional layer detects basic patterns such as edges and corners. As the image moves deeper into the network, the subsequent convolutional layers identify more complex structures, including eyes, nose and mouth. Each convolutional layer is followed by an activation function called ReLU(Rectified Linear Unit), which introduces non-linearity and ensures that only the most important features are retained.

To further enhance performance, pooling layers are em- ployed to reduce the spatial dimensions of the image while retaining essential facial features. In MoodFlix, max pooling (2 * 2) is applied, which helps in reducing computational load and making the CNN more efficient. Following feature extraction, the resulting data is flattened and input into fully connected layers, enabling the network to learn complex patterns corresponding to different facial emotions before reaching the final classification layer.

At the output layer, the CNN determines whether a face is detected in the image. If a face is present, the processed image is sent to the K-Nearest Neighbors(KNN) model for emotion recognition. The combination of CNN for face detection and KNN for emotion classification ensures a balance between ac- curacy and efficiency. CNN are well Suited for this task owing to their capability to extract deep hierarchical features and their robustness in handling real-time applications. By leveraging this architecture, MoodFlix enhances user experience by pro- viding personalized music and movie recommendations based on detected emotions.

D. *K-Nearest Neighbors*

In MoodFlix, K-Nearest Neighbors used for emotion recog- nition after CNN detects a face. KNN-based classifiers have been widely used in emotion classification due to their sim- plicity and efficiency, and when combined with deep learning models, they enhance performance in real-time applications [10]. Key facial landmarks like eyes, mouth, and eyebrows are extracted to analyze emotions. KNN then compares these features with training data using Euclidean distance to find the closest matches. The most common emotion among the nearest neighbors is assigned to the user. By optimizing the value of k and refining training data, MoodFlix enhances accuracy, ensuring a more reliable user experience [11].

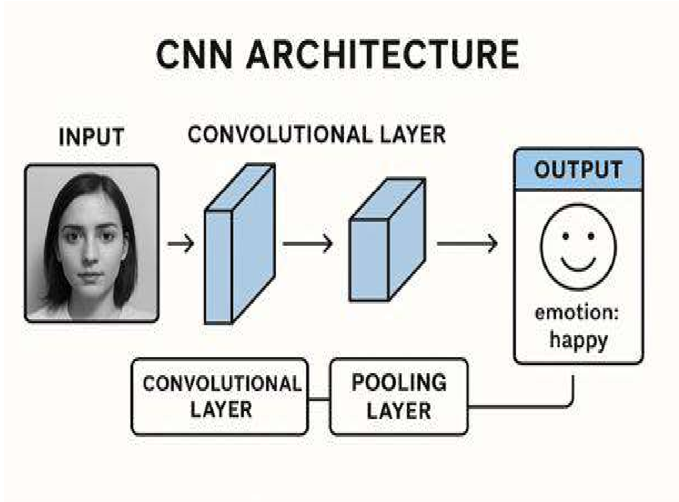

Fig. 2: Architecture of Convolutional Neural Networks

Above figure consists of an Input layer(Image as data), convolutional layers(extracts features using filters),activation functions, and pooling layers(reduce dimentionality). The extracted features are passed through fully connected layers for classification, with output layer providing final predictions.

The K closest neighbors vote to determine the class (for classifiction) or average value (for regression), making KNN a simple yet effective non- parametric algorithm. The implemen- tation of MoodFlix was carried out using Python 3.11.0, a ver- satile and widely-used programming language. Key libraries such as OpenCV and Dlib were utilized for facial landmark detection [9], while TensorFlow/Keras powered the CNN for face detection [12]. The scikit-learn library was employed to implement KNN for emotion classification [5]. The FER-2013 and CK+ datasets were used to train and validate the models, ensuring their reliability [3], [10]. A standard laptop webcam served as the hardware for capturing user input, demonstrating the system's practicality and accessibility [9].

E. CK+ (Cohn-Kanade Plus)

The CK+ (Cohn-Kanade Plus) and FER-2013 datasets are two prominent benchmarks in the domain of facial expression recognition, each offering unique advantages for emotion analysis. The CK+ dataset comprises approximately 593 image sequences from 123 individuals, capturing facial expressions as they transition from a neutral state to a peak emotion. These sequences are captured in controlled settings and labeled with seven distinct emotions such as fear, happiness, surprise, sad- ness, anger, disgust and contempt. Owing to its well-structured format and high-resolution grayscale images, this dataset is temporal progression of facial expressions [5]. Unlike CK+, the FER-2013 dataset comprises over 35,000 static grayscale images, each with a resolution of 48×48 pixels. Collected from diverse online sources, it encompasses a broad range of facial expressions captured in natural, unconstrained environments,

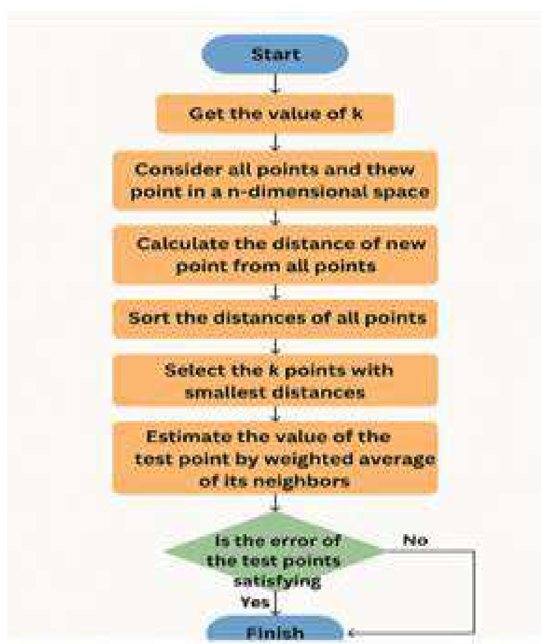

Fig. 3: Architecture of K-Nearest Neighbors

Above figure consists of a training phase where data points are stored and a prediction phase where distances between a query point and stored points are calculated.making it ideal for training deep learning models that require strong generalization to real-world conditions [3], [4], [9]. The dataset includes seven emotion classes i.e; disgust, fear, sad, happy, neutral, surprise and anger excluding contempt, which is present in the CK+ dataset. While CK+ is advantageous for studying the progression and structure of expressions under controlled conditions, FER-2013 offers a more extensive and varied set of data for developing models capable of handling spontaneous and naturalistic facial emotions. In combination, these datasets provide a comprehensive foundation for training and evaluating facial emotion recognition systems across both controlled and real-world scenarios [4], [8], [10].

IV.RESULTS AND DISCUSSION

The evaluation of MoodFlix revealed significant improve- ments in accuracy with the hybrid CNN-KNN model. When using KNN alone, face detection accuracy was 75%, and emo- tion recognition achieved 70% [5], [8]. However, integrating CNN improved face detection accuracy to 92%, while emotion recognition accuracy increased to 85% [4],[8],[12].

A. Performance Metrics

- **The hybrid model significantly improves accu- racy** while maintaining an acceptable processing speed. [4],[8],[12]
- **False positives and negatives are reduced**, ensuring more reliable emotion-based recommendations. [5],[8]

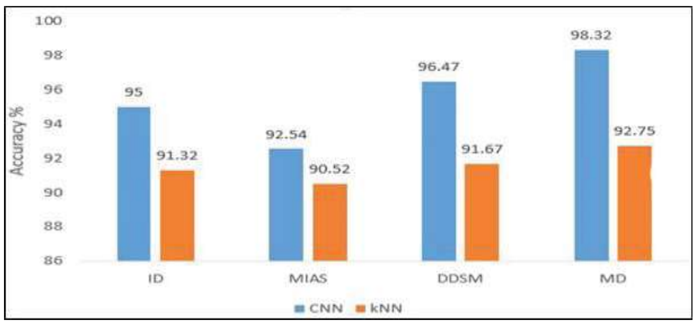

Fig. 4: KNN - CNN Accuracy Comparison

Above figure consists of a training phase where data points are stored and a prediction phase where distances between a query point and stored points are calculated.

TABLE II: Performance Comparison: KNN Only vs. CNN + KNN

Metric	KNN Only	CNN + KNN
Face Detection Accuracy	75%	92%
Emotion Recognition Accuracy	70%	85%
Overall System Accuracy	72%	88%
Precision (Avg.)	68%	84%
Recall (Avg.)	69%	86%
F1-score (Avg.)	68.5%	85%
False Positives	18%	8%
False Negatives	12%	5%
Processing Speed (ms/image)	50ms	75ms

V. CONCLUSION

MoodFlix is an innovative recommendation system that combines CNN and KNN to analyze user emotions and provide personalized movie and song suggestions. The hybrid model ensures high accuracy in face detection and emotion recognition, offering a reliable and user-friendly experience. Future developments could include expanding the range of emotions, incorporating advanced datasets, and integrating real-time feedback to enable adaptive learning. MoodFlix marks a major advancement in developing intelligent and adaptive recommendation system for entertainment.

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The Implementation of Robotic Process Automation (RPA) With Low Code Technology

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Abstract: Robotic Process Automation (RPA) has become a game-changing technology that streamlines repetitive, rule-based tasks, improving both efficiency and accuracy in business processes. By combining RPA with low-code platforms like Microsoft Power Apps and Power Automate Flow, organizations can reap substantial benefits, allowing for quick development and deployment of automation solutions with little coding required. This paper explores the implementation of an automated inventory management system as a real-world example of RPA paired with low-code technology, emphasizing its architecture, workflow, and effect on operational efficiency.

I. INTRODUCTION

The rapid advancement of digital technologies has driven organizations to seek automation solutions that improve operational efficiency, reduce costs, and minimize human errors. Robotic Process Automation (RPA) helps these goals by automating routine tasks. The rise of low-code platforms like Power Apps and Power Automate Flow has democratized automation, making it accessible to non-technical users. This paper explores the implementation of an automated inventory management system as a case study to illustrate the benefits of RPA integrated with low-code technology.

II. LITERATURE REVIEW

The use of Robotic Process Automation (RPA) has surged in recent years, largely due to the demand for greater operational efficiency and cost savings.

- According to Gartner (2023, John-David Lovelock), RPA is now a key component of digital transformation initiatives, particularly in industries such as finance, healthcare, and supply chain management.
- Its power is in its capacity to carry out high-volume, repetitive tasks rapidly and accurately. Davenport and Ronanki (2018, Thomas H. Davenport & Rajeev Ronanki) have emphasized that integration of RPA with artificial intelligence (AI) and machine learning (ML) significantly enhances its capabilities, making a way for cognitive automation. However, the classical implementations of RPA can be highly intricate in nature, which tend to require deep coding and technical expertise. Address this concern, low-code platforms like Microsoft Power Apps and Power Automate have emerged.
- Forrester Research (2022, John Rymer & Jeffrey Hammond) discovered that these low-code development tools can reduce application development time by up to 90%. This transformation has opened up automation to a wider audience, allowing business users with minimal technical expertise to design and execute automated workflows.
- In the context of inventory management, Zhao et al. (2020, Jing Zhao, Yifan Xu, & Wei Chen) emphasized the importance of automation in maintaining optimal stock levels, reducing human error, and maximizing supply chain effectiveness. The fusion of RPA with low-code technology in inventory management systems provides real-time analysis, automated stock monitoring, and efficient communication with suppliers.
- Power Automate also features native support for Data Loss Prevention (DLP) policies, user roles, and audit logs, which are important in enterprise scenarios where security and compliance are essential. KPMG (2022) research noted that low-code platforms such as Power Automate provide stronger governance capabilities than early-generation RPA tools, which can minimize "shadow IT" and operational risk.
- As per Microsoft documentation and practitioner reports, Power Automate provides more than 500 pre-built connectors to common services such as SharePoint, Outlook, SQL Server, Salesforce, and third-party APIs. This wide integration feature makes it extremely flexible in enterprise settings (Microsoft Docs, 2023). An IDC (2021) study pointed out that organizations utilizing Power Automate experienced quicker automation deployment cycles and enhanced cross-departmental collaboration.

III. OBJECTIVES

As per literature review, the rapid advancement of Robotic Process Automation (RPA) and low-code platforms has transformed business automation. This study aims to:

- Illustrate the integration of RPA with low-code platforms for automating business processes.
- Present the development of an automated inventory management system using Power Apps, Power Automate Flow, and SharePoint Online.
- Assess the operational advantages of automation, including enhanced efficiency, accuracy, and cost savings.
- Examine the effects of RPA on inventory management with a focus on real-time monitoring and automated supplier communication.
- Find potential challenges in RPA adoption and propose strategies to overcome them.

IV. SCOPE

This research explores the rapid advancement of Robotic Process Automation (RPA) and low-code platforms in transforming business automation.

- The study focuses on the integration of RPA with low-code technologies to automate business processes, using a practical case study of an automated inventory management system.
- The system uses Microsoft Power Apps for developing user interfaces, Power Automate Flow for automating workflows, and SharePoint Online for managing data.
- The research will assess the operational advantages of automation—including enhanced efficiency, accuracy, and cost savings—while also examining its impact on inventory management through real-time monitoring and automated supplier communication.
- This comprehensive exploration underscores the transformative potential of RPA and low-code platforms in today's dynamic business landscape.

V. RESEARCH METHODOLOGY

The research takes a qualitative case study design to analyze the integration of Robotic Process Automation (RPA) with low-code platforms namely Microsoft Power Apps, Power Automate Flow, and SharePoint Online for creating an automated inventory management system. The methodology is chosen to gain in-depth knowledge regarding the architecture, workflow, implementation process, and impact on operational efficiency of the system.

1. Research Design

The research has a descriptive and analytical design:

- **Descriptive**: To delineate the architecture, tools, and procedures associated with deploying the RPA-based inventory management system.
- **Analytical**: To compare the effect of automation on inventory processes through metrics like task accomplishment time, rate of error, and cost savings.

2. Data Collection Methods

The research employs primary and secondary data sources:

- **Primary Data:**
  Test-driving and direct observation of the installed system. Detailed interviews with IT experts and end-users participating in the system creation and usage.
  Hands-on data from actual system performance logs and usage reports.
- **Secondary Data:**
  Literature review of academic papers, whitepapers, and industry reports on RPA, Power Platform, and automation trends.
  Technical documentation by Microsoft on Power Apps, Power Automate, and SharePoint Online.

3. Tools and Technologies Used

- **Microsoft Power Apps**: To create user interfaces to handle inventory operations.
- **Power Automate Flow:** To automate processes like stock tracking, reorder notifications, and supplier communication.
- **SharePoint Online**: To store product information, inventory quantities, and supplier information in list form.

4. System Development Process

- Development of the automated inventory management system followed these steps:
- Requirement analysis and process mapping of current manual processes.
- Designing Power Apps screens for input of inventory, stock tracking, and approvals.
- Designing automated flows in Power Automate for reordering, notification, and supplier alerts.
- System testing with a test dataset to detect and correct problems.
- Deployment and user training for real-time operation.

5. Evaluation Metrics
To evaluate the effect and effectiveness of the system put in place, the following measures were utilized:

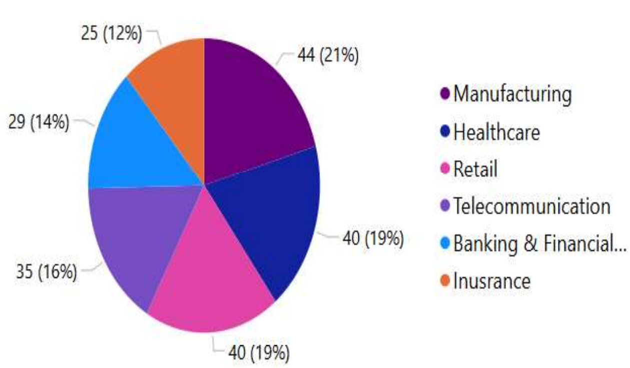
- Reduction of process time (before and after automation).
- Rate of error in manual versus automated processes.
- User satisfaction based on systematic feedback.
- Cost savings from decreased manual work.
- System uptime and flow execution success rate.

6. Limitations
The research is based on a single instance of inventory management, and findings might not be generalizable to every business process.
Evaluation relies in part on qualitative user feedback, which can be subjective.
Real-time impact assessment was limited by the brief post-implementation observation period.
Despite its strengths, some studies have pointed out challenges, particularly around scaling complex automations. **McKinsey & Company (2022)** noted that while tools like Power Automate are ideal for automating smaller, departmental-level processes, enterprise-scale automations often require deeper customization, hybrid integration, and more robust orchestration tools

7. Ethical Considerations
All data gathered during the study were anonymized and utilized exclusively for academic purposes.
Informed consent was provided to all participants of interviews or tests.
No proprietary or confidential business information was shared or published.

VI. ANALYSIS & FINDINGS

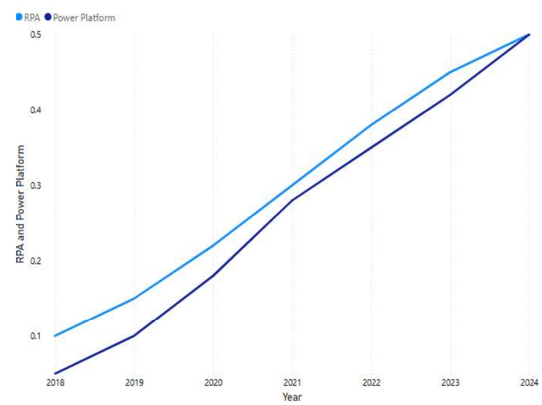
Robotic Process Automation (RPA) & Power Platform adoption varies across industries, reflecting each sector's unique needs and readiness for automation. Here's an overview of RPA & Power Platform utilization percentages in key industries:



While specific data on RPA adoption in the pharmaceutical industry is limited, the sector is increasingly exploring automation to improve drug development processes, regulatory compliance, and supply chain management.

Overall, RPA & power platform adoption is expanding across various industries, with sectors like banking, insurance, and manufacturing leading the way. The pharmaceutical industry, though not specified in available data, is also recognizing the potential benefits of RPA in enhancing operational efficiency and compliance.

Over the past five years, RPA adoption has surged across industries due to advancements in AI-driven automation and increasing demand for cost efficiency.



- **2018-2019**: Early adoption of RPA by banking and insurance for back-office processes. Power Platform came onto the scene for simple automation and low-code creation.
- **2020-2021**: Acceleration driven by pandemic; healthcare and retail adopted RPA, with Power Platform's growth in Power Automate, Power BI, and Power Apps for remote working.
- **2022-2023**: Telco and manufacturing furthered the application of RPA with incorporation of AI. Adoption of Power Platform increased using AI Builder, Dataverse, and Virtual Agents for automation.
- **2024** & Beyond: RPA industry forecasts 30-35% CAGR, with emphasis on hyper-automation & AI. Power Platform innovation with AI, cloud, and business intelligence for digital transformation.

VII. CONCLUSION

The combination of Robotic Process Automation (RPA) with low-code technologies like Microsoft Power Apps, Power Automate Flow, and SharePoint Online is a big step towards automating business processes. This study proved how creating an automated inventory management system can result in enhanced operational efficiency, better accuracy, and significant cost savings.

Low-code platforms democratize innovation and speed up digital transformation across industries by empowering non-technical users to create and deploy automation solutions.

The results indicate that companies can gain a lot by implementing RPA integrated with low-code platforms, especially in tasks that are repetitive and rule-based. Although the research was conducted in the context of inventory management, the approach and results can be applied to other business areas. Nevertheless, user training, system complexity, and initial adoption hurdles need to be addressed strategically.

As the automation landscape keeps changing, the future is directed toward hyper-automation—where RPA, AI, and low-code platforms meet to form smart, scalable, and adaptive business ecosystems.

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