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UNLOCKING HOME AUTOMATION SYSTEM BY FACE DETECTION USING ESP32 CAMERA

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Abstract : The integration of facial recognition technology into home automation systems has emerged as a pivotal advancement in modern security protocols. This project introduces a comprehensive home automation system employing ESP32-CAM, designed to leverage facial detection and recognition for access control. The system comprises an ESP32-CAM module interfaced with a solenoidal lock and a buzzer, orchestrating an intricate interplay between security and accessibility. The primary objective revolves around the discernment between recognized and unrecognized faces. Upon analyzing captured facial data in real-time, the system distinguishes known individuals, granting them access by unlocking the solenoidal lock seamlessly. Simultaneously, an unidentified face triggers an immediate alarm through the buzzer, effectively barring entry by maintaining the lock's secure status.Key components include ESP32-CAM's image capture capabilities, coupled with facial recognition algorithms to swiftly process and identify individuals. The solenoidal lock, controlled by the ESP32-CAM, enforces access permissions based on the recognition outcome, enhancing home security. This project not only demonstrates the technical prowess of ESP32-CAM in facial recognition but also showcases a practical application integrating hardware and software for robust home security. The system's efficiency lies in its ability to differentiate between known and unknown persons, ensuring a secure environment while allowing authorized individuals hassle-free access. This abstract encapsulates the essence of your project, highlighting its core elements, purpose, and contributions in integrating facial recognition technology with home automation for enhanced security measures.

INTRODUCTION

In the landscape of contemporary home security, the fusion of cutting-edge technology and traditional access control mechanisms has become pivotal. With the escalating demand for heightened security measures, the integration of facial recognition technology into home automation systems has emerged as a groundbreaking solution. This project focuses on the implementation of an innovative home automation system utilizing the ESP32-CAM module, orchestrating secure access control through facial detection and recognition.The fundamental aim of this project is to revolutionize traditional access mechanisms by employing facial recognition as a key determinant for granting or denying access. The system integrates an ESP32-CAM module equipped with a camera, interfaced with a solenoidal lock and a buzzer. Leveraging the ESP32-CAM's computational power and image processing capabilities, real-time facial detection and recognition form the crux of this system.Upon detecting a known individual through facial recognition, the system seamlessly unlocks the solenoidal lock, allowing authorized access. Conversely, in the event of an unrecognized face, the system triggers an immediate alert via the buzzer, effectively denying access by maintaining the lock in a secure state.

This project amalgamates hardware components with sophisticated software algorithms, showcasing the ESP32-CAM's prowess in capturing, processing, and analyzing facial data. The synchronization of these elements culminates in a comprehensive home automation system that not only augments security measures but also streamlines access for authorized users.

The significance of this system lies in its ability to create a secure environment by discerning between known and unknown individuals, fortifying homes against unauthorized access while facilitating a seamless entry process for recognized occupants. This introduction provides an overview of the project's objectives, emphasizing the integration of facial recognition technology using the ESP32-CAM module to enhance home security and access control.

FUTURE WORK

The development of a home automation system leveraging facial detection and recognition technology integrated with ESP32-CAM, solenoidal lock, and a buzzer represents a significant stride toward robust and intelligent home security. This innovative system stands as a testament to the fusion of cutting-edge technology and practical implementation for enhanced access control and intruder alert mechanisms. By harnessing the computational power of ESP32-CAM and sophisticated facial recognition algorithms, the proposed system delineates a secure environment by distinguishing known and unknown individuals. The solenoidal lock acts

as the gateway, dynamically granting access solely to recognized faces while promptly denying entry to unidentified persons, ensuring a fortified perimeter against unauthorized intrusion.
The activation of the buzzer serves as an immediate warning upon detection of an unknown face, fortifying security measures by signaling potential breach attempts while maintaining the solenoidal lock in a secure state. This simultaneous execution of access control and alert systems underscores the system's real-time responsiveness and proactive security protocols.
Moreover, the system's design not only emphasizes security but also advocates privacy-conscious operations by internally processing facial data, mitigating external data storage risks. The adaptability and scalability of this solution allow seamless integration with diverse home automation frameworks, presenting opportunities for expansion and integration with other smart home devices based on recognized individuals.

RESEARCH METHODOLOGY
The proposed ADS algorithm uses a GoogleNet-BiLSTM hybrid network as the classifier. This hybrid network requires a video dataset. The video dataset selection criteria, dataset processing, network architecture, the working principle of the network with necessary mathematical interpretation, and the FDS algorithm have been described in this section. The overview of the proposed methodology has been illustrated

LITERATURE REVIEW
We have reviewed the recent and relevant literature on Human Activity Recognition (HAR)-based intelligent secu rity systems. It shows the envious advancement in HAR and its application in various domains [16]. The perfor mance of the HAR system seems to draw the lion's share of researchers' attention, leaving a research gap in its appli cation in the security sector [17]. This paper focuses on applying HAR in intelligence surveillance to strengthen front door security. And the HAR technology is the main engine of this approach. That is why our literature review focuses on advancing HAR using machine learning and its application. A. SMART APPLICATION FOR FRONT DOOR SECURITY B. Sarp et al. used a Raspberry Pi-based video surveillance system to ensure front door security through two features video feed and communication. In their system, the users can monitor the activities in front of the door remotely and also communicate with someone at the front door. They further connected the door through a cellular network to access the functionality in real-time through the internet [18]. While this approach effectively ensures front door security, it has a drawback. And the drawback is the necessity of manual inspection. TheproposedFDSsystemdoesnotrequirehuman intervention to monitor the front door security. It is a fully automatic system that identifies the activities of the individ uals at the front door and alerts the homeowner if anything suspicious happens. Ahomemonitoring system based on ESP32, published by R. C. Aldawira et al., shows the application of IoT to ensure home security, including front door security. This system allows the users to monitor the activities happening inside remotely and outside the house and control the door lock. It also has a motion sensor to sense any motion and alert the users. Moreover, it has a touch sensor that is used to identify human touch on the door knob [19]. These multiple features make the home more secure. However, the system does not use human-like intelligence. Because of using motion and touch sensors, the rate of false alarms is high, and it requires manual adjustment. Compared to this approach, the pro posed FDS is more advanced as it uses CNN and recognizes activities as the human visual cortex does [20]. IoT-based home security systems [21], edge computer-based security systems [22], and intelligent warning-based security sys tems [23] are the commonapproachestoenhancethesecurity of home.Theliterature review demonstrates a research gap in front-door security using a convolutional neural network. The proposed FDS algorithm aims to abridge the gap and utilize CNNsto ensure human-guard-like security at the front door. B. COMPUTER VISION-BASED HAR & APPLICATION Computer vision-based human activity recognition is the dominatingtechnologyinvideoanalysisanditsapplicationin intelligent surveillance, autonomous vehicle, video analysis, video retrieval, and entertainment [24]. The review presented in this paper aligns without observation and methodology. For a front-door security algorithm, a computer vision based machine learning-centered approach is appropriate. V. Mazzia1 et al. developed a short-term posed-based human action recognition system. It achieved 90.86% accuracy with 227,000 parameters [25]. The accuracy of this paper is eye catching, but the computational cost makes it expensive, which is not suitable for developing an affordable security system using this methodology.
rate, so the more volatility will be there in the market if the behaviors of the investors are more sensitive. Plethora (2002)has tested interest rate sensitivity to stock market returns, and concluded an inverse relationship between interest rate and stock returns. Nguyen (2010) studies Thailand market and found thatInterest rate has aninverse relationship with stock prices.

KSE-100 index is used as proxy of market risk. KSE-100 index contains top 100 firms which are selected on the bases of their market capitalization. Beta is the measure of systematic risk and has alinear relationship with return (Horn, 1993). High risk is associated with high return (Basu, 1977, Reiganum, 1981 and Gibbons, 1982). Fama and MacBeth (1973) suggested the existence of a significant linear positive relation between realized return and systematic risk as measured by β. But on the other side some empirical results showed that high risk is not associated with high return (Michailidis et al. 2006, Hanif, 2009). Mollah and Jamil (2003) suggested thatrisk-return relationship is notlinear perhaps due to high volatility.

3.4Statistical tools and econometric models
This section elaborates the proper statistical/econometric/financial models which are being used to forward the study from data towards inferences. The detail of methodology is given as follows.
3.4.1 Descriptive Statistics
Descriptive Statics has been used to find the maximum, minimum, standard deviation, mean and normally distribution of the data of all the variables of the study. Normal distribution of data shows the sensitivity of the variables towards the periodic changes and speculation. When the data is not normally distributed it means that the data is sensitive towards periodic changes and speculations which create the chances of arbitrage and the investors have the chance to earn above the normal profit. But the assumption of the APT is that there should not be arbitrage in the market and the investors can earn only normal profit. Jarque bera test is used to test the normality of data.

3.4.2 Fama-Mcbeth two pass regression

After the test statistics the methodology is following the next step in order to test the asset pricing models. When testing asset pricing models related to risk premium on asset to their betas, the primary question of interest is whether the beta risk of particular factor is priced. Fama and McBeth(1973)develop a two pass methodology in which the beta of each asset with respect to a factor is estimated in a first pass time series regression and estimated betas are then used in second pass cross sectional regression to estimate the risk premium of the factor. According to Blum (1968) testing two-parameter models immediately presents an unavoidable errors-in-the variables problem.It is important to note that portfolios (rather than individual assets) are used for the reason of making the analysis statistically feasible.Fama McBeth regression is used to attenuate the problem of errors-in-variables (EIV) for two parameter models (Campbell, Lo and MacKinlay, 1997).If the errors are in the β (beta)of individual security are not perfectly positively correlated, the β of portfolios can be much more precise estimates of the true β (Blum, 1968).

The study follow Fama and McBeth two pass regressionto test these asset pricing models.The Durbin Watson is used to check serial correlation and measures the linear association between adjacent residuals from a regression model. If there is no serial correlation, the DW statistic will be around 2. The DW statistic will fall if there is positive serial correlation (in worst case, it will be near zero). If there is a negative correlation, thestatistic will lie somewhere between 2 and 4. Usually the limit for non-serial correlation is considered to be DW is from 1.8 to 2.2. A very strong positive serial correlation is considered at DW lower than 1.5 (Richardson and smith, 1993).

According to Richardson and smith(1993) to make the model more effective and efficient the selection criteria for the shares in the period are: Shares with no missing values in the period, Shares with adjusted $R^2 < 0$ or F significant (p-value) >0.05of the first pass regression of the excess returns on the market risk premium are excluded. And Shares are grouped by alphabetic order into group of 30 individual securities (Roll and Ross, 1980).

3.4.2.1 Model for CAPM

In first pass the linear regression is used to estimate beta which is the systematic risk.

$$R_i - R_f = (R_m - R_f)\beta \qquad (3.1)$$

Where $R_i$isMonthly return of thesecurity, R_f isMonthly risk free rate, R_m isMonthly return of market and βis systematic risk (market risk).

The excess returns R_i - R_f of each security is estimated from a time series share prices of KSE-100 index listed shares for each period under consideration. And for the same periodthe market Premium R_m - $R_f$also estimated. After that regress the excess returns R_i - R_f on the market premium R_m - $R_f$to find the beta coefficient (systematic risk).

Then a cross sectional regression or second pass regression is used on average excess returns of the shares and estimated betas.

$$\hat{R}_i = \gamma_0 + \gamma_1\beta_1 + \epsilon \qquad (3.2)$$

Where $ƛ_0$= intercept, $\hat{R}_I$is average excess returns of security i,$\beta_I$isestimated be coefficient of security I and Є is error term.

3.4.2.2 Model for APT

In first pass the betas coefficients are computed by using regression.

$$R_i - R_f = \beta_i f_1 + \beta_{i2} f_2 + \beta_{i3} f_3 + \beta_{i4} f_4 + \epsilon \qquad (3.3)$$

Where Ri is the monthly return of stock i,R_f is risk free rate, β_i is the sensitivity of stock i with factors and ϵ is the error term.

Then a cross sectional regression or second pass regression is used on average excess returns of the shares on the factor scores.

$$\hat{R} = \gamma_0 + \gamma_1\beta_1 + \gamma_2\beta_2 + \gamma_3\beta_3 + \gamma_4\beta_4 + \epsilon_i \qquad (3.4)$$

Where$\hat{R}$ is average monthly excess return of stock I, ƛ = risk premium, β_1 to β_4 are the factors scores and ε_i is the error term.

3.4.3 Comparison of the Models

The next step of the study is to compare these competing models to evaluate that which one of these models is more supported by data.This study follows the methods used by Chen (1983), the Davidson and Mackinnon equation (1981) and the posterior odds ratio (Zellner, 1979) for comparison of these Models.

3.4.3.1 Davidson and MacKinnon Equation

CAPM is considered the particular or strictly case of APT. These two models are non-nested because by imposing a set of linear restrictions on the parameters the APT cannot be reduced to CAPM. In other words the models do not have any common variable. Davidson and MacKinnon (1981) suggested the method to compare non-nested models. The study used the Davidson and MacKinnon equation (1981) to compare CAPM and APT.

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IV. RESULTS AND DISCUSSION

The prototype implementation of the hardware is carried out in this section. A Microcontroller as the central processing unit, receiving data from sensors including . When the system detects unfavorable conditions, the Buzzer triggers alerts, enabling timely interventions to optimize crop growth..

4.1 Results of Descriptive Statics of Study Variables
Table 4.1: Descriptive Statics

Table 4.1 displayed mean, standard deviation, maximum minimum and jarque-bera test and its p value of the macroeconomic variables of the study. The descriptive statistics indicated that the mean values of variables (index, INF, EX, OilP and INT) were 0.020, 0.007, 0.003, 0.041 and 0.047 respectively. The maximum values of the variables between the study periods were 0.14, 0.02, 0.04, 0.41, 0.11 and 0.05 for the KSE- 100 Index, inflation, exchange rate, oil prices and interest rate.
The standard deviations for each variable indicated that data were widely spread around their respective means.
Column 6 in table 4.1 shows jarque bera test which is used to checkthe normality of data. The hypotheses of the normal distribution are given;
H_0 : The data is normally distributed.
H_1 :The data is not normally distributed.
Table 4.1 shows that at 5 % level of confidence, the null hypothesis of normality cannot be rejected. KSE-100 index and macroeconomic variables inflation, exchange rate, oil prices and interest rate are normally distributed.
The descriptive statistics from Table 4.1 showed that the values were normally distributed about their mean and variance. This indicated that aggregate stock prices on the KSE and the macroeconomic factors, inflation rate, oil prices, exchange rate, and interest rate are all not too much sensitive to periodic changes and speculation. To interpret, this study found that an individual investor could not earn higher rate of profit from the KSE. Additionally, individual investors and corporations could not earn higher profits and interest rates from the economy and foreign companies could not earn considerably higher returns in terms of exchange rate. The investor could only earn a normal profit from KSE.

Table 1 Table Type Styles

I. ACKNOWLEDGMENT

Thepreferredspellingoftheword "acknowledgment" inAmericaiswithoutan "e" afterthe "g".Avoidthestiltedexpression, "Oneofus(R.B.G.)thanks..." Instead,try"R.B.G.thanks".Putapplicablesponsoracknowledgmentshere;DONOTplacethemonthefirstpageofyourpaperorasafootnote.

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