



INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

SECURED ONLINE TRANSACTION WITH DEEP LEARNING

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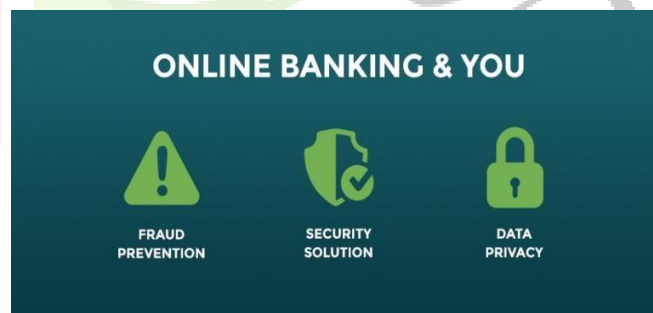
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Abstract: Net banking is now very popular among consumers because it provides a convenient way to perform transactions from anywhere using smart devices. The ultimate goal is an authentication system that validates user for accessing the system only with correct input (password). In existing way there would be negligible chances of botor anyone to crack passwords even if they have cracked the first level or second level, it would be impossible to crack the third one. Here Convolutional neural network (CNN) algorithm used for password matching process. This also provides OTP verification process in reverse order. Hence while creating the technology the emphasis was put on theuse of innovative and nontraditional methods. Many users find the most widespread text-based password systems unfriendly, so in the case of three level passwords it is tried by creating a simple user interface and providing users with the best possible comfort in solving password.

Keywords: Net banking, Convolutional Neural Network, Text-based password

I. INTRODUCTION

DEEP LEARNING: Deep learning is a machine learning technique that teaches computers to do what comes naturally to humans: learn by example. Deep learning is a key technology behind driverless cars, enabling them to recognize a stop sign, or to distinguish a pedestrian from a lamppost.



It is the key to voice control in consumer devices like phones, tablets, TVs, and hands-free speakers. Deep learning is getting lots of attention lately and for good reason. It's achieving results that were not possible before. In deep learning, a computer model learns to perform classification tasks directly from images, text, or sound. Deep learning models can achieve state-of-the-art accuracy, sometimes exceeding human-level performance. Models are trained by using a large set of labeled data and neural network architectures that contain many layers. Deep learning achieves recognition accuracy at higher levels than ever before. This helps consumer electronics meet user expectations, and it is crucial for safety-critical applications like driverless cars. Recent advances in deep learning have improved to the point where deep learning outperforms humans in some tasks like classifying objects in images. While deep learning was first theorized in the 1980s, there are two main reasons it has only recently become useful: Deep learning requires large amounts of labeled data. For example, driverless car development requires millions of images and thousands of hours of video.

II. APPLICATIONS OF DEEP LEARNING

Deep learning applications are used in industries from automated driving to medical devices.

Automated Driving: Automotive researchers are using deep learning to automatically detect objects such as stop signs and traffic lights. In addition, deep learning is used to detect pedestrians, which helps decrease accidents.

Aerospace and Defense: Deep learning is used to identify objects from satellites that locate areas of interest, and identify safe or unsafe zones for troops.

Medical Research: Cancer researchers are using deep learning to automatically detect cancer cells. Teams at UCLA built an advanced microscope that yields a high-dimensional data set used to train a deep learning application to accurately identify cancer cells.

Industrial Automation: Deep learning is helping to improve worker safety around heavy machinery by automatically detecting when people or objects are within an unsafe distance of machines.

Electronics: Deep learning is being used in automated hearing and speech translation. For example, home assistance devices that respond to your voice and know your preferences are powered by deep learning applications.

III. DEEP LEARNING FUNCTIONALITY

Most deep learning methods use neural network architectures, which is why deep learning models are often referred to as deep neural networks. The term “deep” usually refers to the number of hidden layers in the neural network. Traditional neural networks only contain 2-3 hidden layers, while deep networks can have as many as 150. Deep learning models are trained by using large sets of labeled data and neural network architectures that learn features directly from the data without the need for manual feature extraction. One of the most popular types of deep neural networks is known as convolutional neural networks (CNN or ConvNet). A CNN convolves learned features with input data, and uses 2D convolutional layers, making this architecture well suited to processing 2D data, such as images. CNNs eliminate the need for manual feature extraction, so you do not need to identify features used to classify images. The CNN works by extracting features directly from images. The relevant features are not pretrained; they are learned while the network trains on a collection of images. This automated feature extraction makes deep learning models highly accurate for computer vision tasks such as object classification. CNNs learn to detect different features of an image using tens or hundreds of hidden layers. Every hidden layer increases the complexity of the learned image features. For example, the first hidden layer could learn how to detect edges, and the last learns how to detect more complex shapes specifically catered to the shape of the object we are trying to recognize. A key advantage of deep learning networks is that they often continue to improve as the size of your data increases.

The three most common ways people use deep learning to perform object classification are:

Training from Scratch

To train a deep network from scratch, you gather a very large labeled data set and design a network architecture that will learn the features and model. This is good for new applications, or applications that will have a large number of output categories. This is a less common approach because with the large amount of data and rate of learning, these networks typically take days or weeks to train.

Transfer Learning

Most deep learning applications use the transfer learning approach, a process that involves fine-tuning a pretrained model. You start with an existing network, such as AlexNet or GoogleNet, and feed in new data containing previously unknown classes. After making some tweaks to the network, you can now perform a new task, such as categorizing only dogs or cats instead of 1000 different objects. This also has the advantage of needing much less data (processing thousands of images, rather than millions), so computation time drops to minutes or hours.

Feature Extraction

A slightly less common, more specialized approach to deep learning is to use the network as a feature extractor. Since all the layers are tasked with learning certain features from images, we can pull these features out of the network at any time during the training process. These features can then be used as input to a machine learning model such as support vector machines (SVM).

IV. PREDICTIVE ANALYSIS

Predictive analytics uses historical data to predict future events. Typically, historical data is used to build a mathematical model that captures important trends. That predictive model is then used on current data to predict what will happen next, or to suggest actions to take for optimal outcomes.

Predictive analytics has received a lot of attention in recent years due to advances in supporting technology, particularly in the areas of big data and machine learning.

Predictive analytics is often discussed in the context of big data, Engineering data, for example, signals come

from sensors, instruments, and connected systems out in the world. Business system data at a company might include

transaction data, sales results, customer complaints, and marketing information. Increasingly, businesses make data-

driven decisions based on this valuable trove of information. To extract value from big data, businesses apply

algorithms to large data sets using tools such as Hadoop and Spark.

The data sources might consist of transactional databases, equipment log files, images, video, audio, sensor, or other types of data. Innovation often comes from combining data from several sources.

With all this data, tools are necessary to extract insights and trends. Machine learning techniques are used

to find patterns in data and to build models that predict future outcomes. A variety of machine learning algorithms

are available, including linear and nonlinear regression, neural networks, support vector machines, decision trees,

and other algorithms.

Predictive analytics helps teams in industries as diverse as finance, healthcare, pharmaceuticals, automotive, aerospace, and manufacturing.

- Automotive – Breaking new ground with autonomous vehicles
 - Companies developing driver assistance technology and new autonomous vehicles use predictive analytics to analyze sensor data from connected vehicles and to build driver assistance algorithms.
- Aerospace – Monitoring aircraft engine health
 - To improve aircraft up-time and reduce maintenance costs, an engine manufacturer created a real-time analytics application to predict subsystem performance for oil, fuel, liftoff, mechanical health, and controls.
- Energy Production – Forecasting electricity price and demand
 - Sophisticated forecasting apps use models that monitor plant availability, historical trends, seasonality, and weather.
- Financial Services – Developing credit risk models
 - Financial institutions use machine learning techniques and quantitative tools to predict credit risk.
- Industrial Automation and Machinery – Predicting machine failures
 - A plastic and thin film producer saves 50,000 Euros monthly using a health monitoring and predictive maintenance application that reduces downtime and minimizes waste.

- **Medical Devices** – Using pattern-detection algorithms to spot asthma and COPD. An asthma management device records and analyzes patients' breathing sounds and provides instant feedback via a smart phone app to help patients manage asthma and COPD.

Predictive analytics is the process of using data analytics to make predictions based on data. This process uses data along with analysis, statistics, and machine learning techniques to create a predictive model for forecasting future events.

The term “predictive analytics” describes the application of a statistical or machine learning technique to create

a quantitative prediction about the future. Frequently, supervised machine learning techniques are used to predict a

future value (How long can this machine run before requiring maintenance?) or to estimate a probability (How likely

is this customer to default on a loan?). Predictive analytics starts with a business goal: to use data to reduce waste,

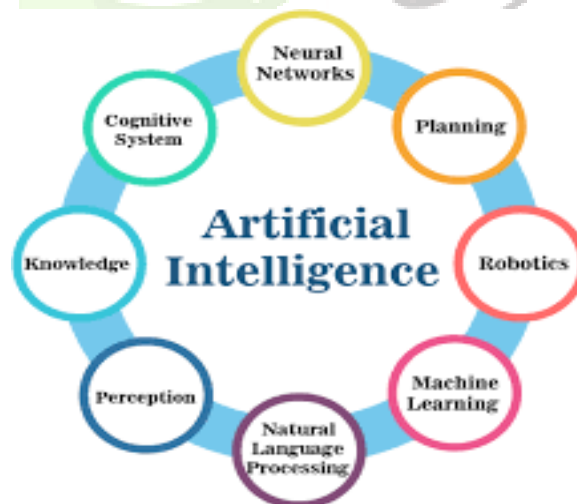
save time, or cut costs. The process harnesses heterogeneous, often massive, data sets into models that can generate

clear, actionable outcomes to support achieving that goal, such as less material waste, less stocked inventory, and

manufactured product that meets specifications.

V. ARTIFICIAL INTELLIGENCE

Artificial intelligence, or AI, is a simulation of intelligent human behaviour. It's a computer or system designed to perceive its environment, understand its behaviours, and take action. Consider self-driving cars: AI-driven systems like these integrate AI algorithms, such as machine learning and deep learning, into complex environments that enable automation. Data preparation requires domain expertise, such as experience in speech and audio signals, navigation and sensor fusion, image and video processing, and radar and lidar. Engineers in these fields are best suited to determine what the critical features of the data are, which are unimportant, and what rare events to consider. AI also involves prodigious amounts of data. Yet labeling data and images is tedious and time-consuming. Sometimes, you don't have enough data, especially for safety-critical systems. Generating accurate synthetic data can improve your data sets. In both cases, automation is critical to meeting deadlines.



Deployment

AI models need to be deployed to CPUs, GPUs, and/or FPGAs in your final product, whether part of an embedded or edge device, enterprise system, or cloud. AI models running on the embedded or edge device provide the quick results needed in the field, while AI models running in enterprise systems and the cloud provide results from data collected across many devices. The deployment process is accelerated when you generate code from your models and target your devices. Using code generation optimization techniques and

hardware-optimized libraries, you can tune the code to fit the low power profile required by embedded and edge devices or the high-performance needs of enterprise systems and the cloud.

Reinforcement Learning

In control systems that benefit from learning based on cumulative reward, reinforcement learning is an ideal technique. Reinforcement Learning Toolbox™ lets you train policies using DQN, A2C, DDPG, and other reinforcement learning algorithms. You can use these policies to implement controllers and decision-making algorithms for complex systems such as robots and autonomous systems. You can implement the policies using deep neural networks, polynomials, or lookup tables. Reinforcement learning is a type of machine learning technique where a computer agent learns to perform a task through repeated trial and error interactions with a dynamic environment. This learning approach enables the agent to make a series of decisions that maximize a reward metric for the task without human intervention and without being explicitly programmed to achieve the task. AI programs trained with reinforcement learning beat human players in board games like Go and chess, as well as video games. While reinforcement learning is by no means a new concept, recent progress in deep learning and computing power made it possible to achieve some remarkable results in the area of artificial intelligence. Reinforcement learning is a branch of machine learning (Figure 1). Unlike unsupervised and supervised machine learning, reinforcement learning does not rely on a static dataset, but operates in a dynamic environment and learns from collected experiences. Data points, or experiences, are collected during training through trial-and-error interactions between the environment and a software agent. This aspect of reinforcement learning is important, because it alleviates the need for data collection, preprocessing, and labeling before training, otherwise necessary in supervised and unsupervised learning. Practically, this means that, given the right incentive, a reinforcement learning model can start learning a behavior on its own, without (human) supervision. Deep learning spans all three types of machine learning; reinforcement learning and deep learning are not mutually exclusive. Complex reinforcement learning problems often rely on deep neural networks, a field known as deep reinforcement learning. Deep neural networks trained with reinforcement learning can encode complex behaviors. This allows an alternative approach to applications that are otherwise intractable or more challenging to tackle with more traditional methods. For example, in autonomous driving, a neural network can replace the driver and decide how to turn the steering wheel by simultaneously looking at multiple sensors such as camera frames and lidar measurements. Without neural networks, the problem would normally be broken down in smaller pieces like extracting features from camera frames, filtering the lidar measurements, fusing the sensor outputs, and making “driving” decisions based on sensor inputs. While reinforcement learning as an approach is still under evaluation for production systems, some industrial applications are good candidates for this technology.

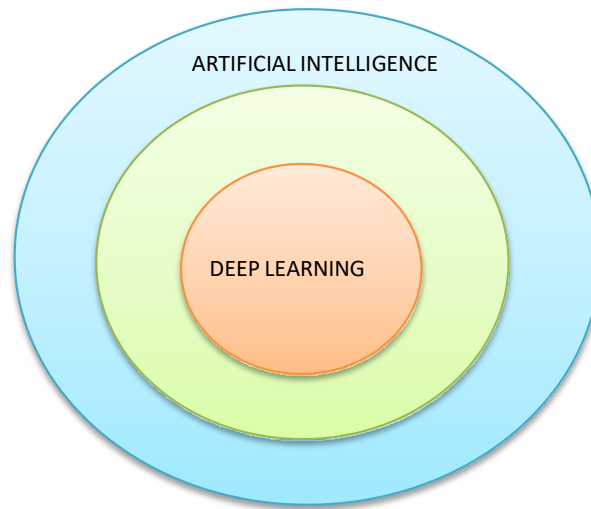
Advanced controls: Controlling nonlinear systems is a challenging problem that is often addressed by linearizing the system at different operating points. Reinforcement learning can be applied directly to the nonlinear system.

Automated driving: Making driving decisions based on camera input is an area where reinforcement learning is suitable considering the success of deep neural networks in image applications.

Robotics: Reinforcement learning can help with applications like robotic grasping, such as teaching a robotic arm how to manipulate a variety of objects for pick-and-place applications. Other robotics applications include human-robot and robot-robot collaboration.

Scheduling: Scheduling problems appear in many scenarios including traffic light control and coordinating resources on the factory floor towards some objective. Reinforcement learning is a good alternative to evolutionary methods to solve these combinatorial optimization problems.

Calibration: Applications that involve manual calibration of parameters, such as electronic control unit (ECU) calibration, may be good candidates for reinforcement learning.



VI. CONCLUSION

Biometric technology offers enhanced security while being convenient to use. It guarantees that information is accessed only by authorized persons. The security system offers a reliable method for authenticating users. It is a robust solution to meet the stringent requirements of restricted access for top secret information. Significantly, it reduces frauds and minimizes password administrator costs. When biometric technology goes main-stream, banks can use biometrics in every transaction requiring the authentication of identity. Iris recognition is one of the most accurate security systems to identify a unique user, promptly and conveniently. As the level of security breaches and transaction frauds increase day by day, the need for highly secure identification and personal verification information systems is becoming extremely important especially in the banking and finance sector. In this project, we can implement a face recognition system to online net-banking application in AI environments. Face Recognition features can be used to make net-banking systems more secure for authentication purposes in banking-based security systems. The ID can be stolen; passwords can be forgotten or cracked but the physical characteristics of a person cannot be stolen or hacked. The Face Recognition identification overcomes all the above. And also provides multi-person access control to provide access privileges to users with improved security. Real-time alert system about unauthorized access and multi-person access.

VII. SCOPE FOR FUTURE PROSPECTS

In future, the framework can be extended to implement a net banking security by using fingerprint recognition and GSM MODEM took advantages of the stability and reliability of fingerprint characteristics. Additionally, the system also contains the original verifying methods which were inputting owner's password which is sent by the controller. The security features were enhanced largely for the stability and reliability of owner recognition. The whole system was built on the technology of embedded system which makes the system more safe, reliable and easy to use.



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