DEEP LEARNING TO PROTECT PLANTS Using Technology

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Abstract In India, Banana is the second most significant natural product crop close to mango. Its all year availability, reasonableness, varietal range, taste, nutritive and restorative worth makes it the most loved organic product among all classes of individuals. Developing sound banana is confronting critical difficulties on overall revenue. Dynamic in Plantain tree development need exceptional consideration for ensuring their yields and accordingly making their development more productive. The supplements, water and daylight are taken by the weeds from the harvests. Additionally, the effect of different sicknesses and bugs on banana creation are pulverizing. To secure their banana crops, numerous dynamic each day must be taken by the ranchers. Harvest Protection, identification and expectation procedures manage the acts of ranchers used to safeguard their yields against weeds, in-organizations and illnesses. Rural Data got from heterogeneous sources show the Big Data characteris-spasms like high volume, high speed, and high veracity. Different Deep Learning procedures are observed to be reasonable for investigating these information and accomplish the data with respect to the presence of weeds, the seriousness of illnesses and the contaminations brought about by bugs at its beginning phase. It assists with suggesting the prudent steps for every one of these issues.This survey assists the analysts with finding out about the presently utilized DL methods for crop security, which will help them for discovering most precise DL procedure for their harvests.

Keywords: Agriculture, Big Data Analytics, Convolutional Neural Network, Crop Protection, Deep Learning,Plantain Tree Cultivation

1. Introduction

In Indian economy, agriculture is the mainstay. It is an inevitable sector which has provided food and income for millions of people. Thus, it supports Indian economy as well. Plantain trees are the one of the major crops which has the capability of providing huge income to the farmers. Banana is the second most important fruit crop next to mango in India. Among all classes of people, banana is the most favorite fruit, since its affordability, taste, year-round availability, nutritive and medicinal value. Export potential of banana is also high. It has also good export potential. In India, while comparing with other fruit crops, the production of banana is in the first position and its area of cultivation is in the third position. Cultivating healthy banana is facing significant challenges on profit margin. Plantain is an herbaceous perennial belonging to the family Musaceae. Plantains and the cultivated varieties are derived from ancestors who are originated from the Malaysian peninsula, New Guinea and South-East Asia[1].

Farmers are not able to enjoy the income capability from plantain tree cultivation fully because there are various threats such as diseases and pests, which reduces the banana production and leads to huge financial loss. In this situation, Crop Protection techniques are inevitable for increasing the yield of the plantain tree. Crop protection techniques deals with the practices of farmers used to defend their crops against weeds, insects, and diseases. The nutrients, water and sunlight are stolen by the weeds from the crops. Also, the impact of various diseases and insects on banana production is devastating. Early stage detection and diagnosis of plant diseases help farmers to control the severity of the disease. Indicators of these diseases and pests are diverse. In early stage itself, some crops have visible disease symptoms, and some crops shows symptoms at later stages only as there will be no option to save the crop.

To identify the diseases and pests in early stage itself, constant one-to-one care over the plants will help a lot. It also assures minimized yield loss and sustains the plant quality. Unawareness of the farmers for the identifying diseases from the symptoms on the plants necessitates the development of automated systems for providing diagnos- tic services.

In the forthcoming sections, challenges in plantain tree cultivation, the role of AI in plantain tree cultivation, the support of big data and deep learning techniques for plantain tree protection are surveyed from the past researches and are presented in the easily understandable format.

2. Challenges in Plantain Tree Cultivation

Banana crop face various diseases start from its initial stage. Most of the symptoms are expressed on leaf, stem, flowers, fruits, roots and suckers. Major plantain tree diseases, their symptoms, cause and control measures are dis- cussed in table 1.

Table 1. Major Plantain tree diseases, Symptoms, Cause and Control measures [2,3]

Dis- eases	Symptoms	Cause	Control	Image
Anthrac - nose	Black lesions on green fruit, Brown/black spots on fruit peels.	Fungus	Recommended to Spray Bavistin (1%) and Chlorothalonil (0.2%) four times at 15 days break. Prompt cool- ing, minimizing bruising and proper sanitation of handling are also helps to minimize the disease.	
Black siga- toka/Yel- low siga- toka	Brown/red flecks or spots on topside/underside of the leaves, death of leaf surface, bunch not developing spots with grey center and dark/yel- low border.	Fungus	Recommend the regular applica- tions of fungicides, remove leaves with mature spots, rice plant spacing for reduce humidity and improving air circulation.	
Panama disease	Older leaves are yellowing, leaf sheaths are splitting, leaves buckling and wilting, death of entire canopy.	Fungus	Recommend the utilization of dis- ease-free seed pieces, there is no ef- fective treatment, once plants got in- fected.	
Rhizome rot	Break of pseudo stem from rhizome, Non germination of rhizome, brown/yellow and watery nature of internal tissue	Bacteria	Recommend the selection of dis- ease-free and high-quality rhizomes for propagation, the regular disinfec- tion of each propagation tools. Dry- ing of the seed pieces before plant- ing.	
Bunchy top	Leaf margins become chlo- rotic and upturned, Dark green streaks found in leaves, leaves will erect and brittle, not pro- ducing bunches and has a ‘brunchy top’.	Virus	Plantation of less susceptible varie- ties, abolish disease-ridden plants for preventing the blowout of the disease.	

Moko disease	Wilted, chlorotic and collapsing older leaves, collapsing of pseudo stem, entire canopy spread.	Bacterium	Recommend Regular monitoring is necessary to find the presence of dis- ease, removal of male buds, disin- fection of the tools and destroy the infected and neighboring plants, if Moco is found to be present.	
Tip over or bacterial soft rot	Known as young suckers, leads to rotting and emitting of foul odor, found Bunchy top/curly top, Collar regions are getting rotten, water soaked yellow/dark brown cortex areas are more in. yellowish to reddish ooze is happened to see, while cutting the affected plants at the collar region.	Bacterium	High humidity and temperature are ideal growing conditions for the bac- teria. Bacteria survive in crop debris. It gets worse in hot weather, spread through contaminated water and the water splash from the damaged tis- sues.	
Banana bract mosaic	Rod shaped pinkish to reddish streaks on midrib, pseudo stem and peduncle, mild mosaic streaks on bracts, peduncle and fingers, at emergence and sep- aration of leaf sheath from cen- tral axis suckers exhibit unu- sual reddish-brown streaks, leaves are clustered at crown with a traveler's palm appear- ance, elongated peduncle and half-filled hands.	Virus	Recommend the control of suckers in the field. The disease is spreading mainly through aphid vectors such as Aphis gosypii, Pentolonianigro- nervosa and Rhopalosiphummaidis.	
Banana streak	Leaves shows yellow streaking and progressing to a black streaked appearance in older leaves because of excess necrotic.	virus	Recommend the disinfection of the planting materials because bugs such as Planococcuscitri, Saccharicoccussacchari are transmited through it.	
Infectiou s chlorosis	The disease occurs in all stages of banana growth. Striped ap- pearance of leaves since light- yellow streaks from mid rib to edge of the blade are found in leaf veins.	Virus	Virus is disseminated by suckers and Aphis gossypi.	
Cigar End Tip Rot	The rotted portion of the banana finger is getting dried with a black necrosis and spreads to fruits.	Fungus	Recommend prompt cooling, proper sanitization and the removal of the pistil and perianth by hand 8-10 days after bunch formation, Dithane M - 45 (0.1%) or Topsin M (0.1%) spray reduces the spread of the disease.	
Crown Rot	The crown tissues become black and spreads to the pulp through the pedicel, leads to the separation of fingers from the hand	Fungus	Dipping the bunches or hands in Thiobendazole or Benomyl and/or using fungicide impregnated cellulose pad for packing is recommended.	
Stem-end Rot	The flush of the fingers be- comes water-soaked and soft.	Fungus	Recommend prompt cooling, disinfection of handling facilities and hot water treatment of hands.	

Pseu-dostem Heart Rot	Lamina missing or decayed heart leaves, The color of the inner leaves from yellow to brown and then die.	Fungus	Recommend proper spacing, field sanitation and good drainage. Use of spraying of Captan or Dithane M-45 or Dithane Z- 78 sprays reduces the spread of the disease effectively.	
Head Rot	Rotten and foul odor. In older plants rotten leaf base and col-lar region, swollen and split trunk bases.	Fungus	Recommend the conditioning of the soil and good drainage, to prevent the disease utilize the rhizomes with active central buds and dead lateral buds.	
Banana aphid	Distorted plants with curled, shriveled leaves, colonies of aphids found in plant crowns, the color of the aphid's varies from brown to black color.	In-sect/pest	Recommend the spraying of insecti- cidal soaps to control aphid popula- tions, remove and destroy the in- fected plants for preventing the spread.	
Rhizome weevil	Reduced fruit production and plant growth, round tunnels and holes is visible in corm up to 8 mm in diameter, root de-struction and death of plants, adult insect found between leaf heaths.	In-sect/pest	Recommend to plant healthy plant materials with no visible tunnels, hot water treatment helps for killing grubs and eggs, neem powder treat-ment and appropriate insecticides is helping to control the numbers of weevils.	
Coconut scale	Discolored and yellow plant tissues, flat/small/whitish scales on undersides of leaves, peduncles, petioles and fruit.	In-sect/pest	Recommend biological control with lady beetles for scale management.	
Pseudo stem Borer	Exudation and blackening on the plant sap and gradually plant dies, the brown or black pests are active in monsoon and summer.	In-sect/pest	Recommend clean cultivation and the use of Celphos tablets for the ef-fective control of larva/egg/pupa/adult insect popula-tion by placing the tablet inside the pseudo stem and plastered with mud. Severely infected plants must be uprooted and burnt.	
Fruit and Leaf Scarring Beetle	Underdevelopment of the fruits and leaves because the beetles feed the young leaves and fruit skin, mostly found in the rainy season.	In-sect/pest	Recommend the exclusion of grass and weeds from plantations.	
Burrow-ing Nem-atode	Dark and small spot on the root due to the egg deposit by the nematode and the hatching lar- vae is eating the roots that damages the root tissues. Re-duction in size and number of fruits. Not responding to ferti-lizer and other cultural prac-tices.	In-sect/pest	Recommend the usage of nemati-cides especially granular nemati-cides combined with fertilizers as the control measure, use nematode-free corms in fallow soil.	

3. Role of Artificial Intelligence in Plantain Tree Cultivation

Usage of AI in agricultural robotics, predictive analytics, soil and crop monitoring leads to the digitization of agricultural sector. Farmers are familiar with the farm management systems for better processing and analysis of sensor, satellite, weather and soil sampling data by utilizing customized AI software. Globally the use of AI, particularly Machine Learning (ML) and Deep Learning (DL) have already proved his role in agriculture. Blue River technology, a US based company has evolved DL model for detecting weeds, their type and choosing the right herbicides for the plants. The machines can be taught about different weeds using the images from Cameras and sensors using DL techniques [4]. Then the encroachment area found, and the right herbicides are sprayed precisely. The rich set of scientific resources and the world's best research institutions of India has the capability to provide an AI software which can solve the issues faced by the farmers. The expensiveness of AI and other emerging technologies makes them unaffordable to the debt-ridden farmers and other common people.

ML and DL have transformative role in agriculture and smart farming systems [4]. Traditionally, Farmers have been managed many issues in the farming system with their own expertise and experience. This may include soil management, selection of harvesting practices, managing plant diseases, pests and weeds. Smart farming systems use advanced sensing techniques such as proximal, airborne and satellite-based image sensors along with the traditional sensors for capturing agricultural data. Well-organized storage and analytics resolutions are needed to be developed for handling the data produced through those real-time sensing and instrumentation platforms. The massive volume, velocity and variety of data produced from the sensors and real-time platforms in smart farming systems lead to a problem termed as 'Big Data'.

Once the relevant data have been captured, knowledge needed for farmers can be extracted through data analytics. The standard traditional statistical methods, such as regression, ANOVA (Analysis of Variance) and PCA (Principal Component Analysis) are used in agricultural applications conventionally. These are inadequate to deal with Big Data applications. This leads to the adoption of appropriate DL model (e.g. Convolution Neural Network (CNN), Recurrent Neural Network (RNN)) and train them with suitable algorithm (e.g. a gradient descent method) by ensure privacy [5].

4. Big Data and Deep Learning for Plantain Tree Protection

Nowadays, the use of Big Data concept has become prominent in various economic and agricultural sectors. Big Data is generally denoting to complex, large, diverse, distributed or longitudinal datasets made from a variety of available sources (sensors, instruments, other digital sources or internet transactions) and in the future that are being accrued in such vast quantities which will be unbearable to manage using traditional analysis techniques [6].

Within agriculture, the bigdata can be generated from geospatial datasets, sensors, digital devices connected to the Cloud via the IOT and from already collected farm compliance data. The proper analysis of the available agricultural Big Data can provide solutions to an enormous number of thought-provoking enquiries of the farmers which could be capable of agricultural decision making with an eye to future trends [7].

Crop protection is the science and practice to manage the weeds/pests/plant diseases. Apt identification of diseases, pests and weeds in agriculture system helps farmers for controlling and managing them properly. Automatic plant disease identification and classification is also an inevitable area that necessitates the development of DL models for processing agricultural Big Data. In the past decades, different combination of image acquisition methods, image enhancement methods, image segmentation methods and feature extraction methods using DL have been attempted for disease identification and classification [8,9].

This section explores the role of Big Data and various DL techniques used for the detection and prediction of Diseases/pests/weeds for the protection of crops generally.

4.1 Big Data Analytics and Crop Protection

The five major characteristics of Big Data are large volume, velocity, variety, veracity and valorization which are described in table 2. The 5V's: Volume refers to size, variety refers to the multiple data sources, formats, variables and heterogeneity (unstructured/structured), velocity states the acquiring frequency (seconds to years), veracity indicates the uncertainty and inconsistency and valorization indicates the propagation of the data [10]. The first 3 characteristics (volume, velocity and valorization) of Big Data are more challenging and getting more attention nowadays [11].

The agricultural data for Crop Protection shows the characteristics of the Big Data in nature and are originated from many sources. Agricultural data can describe the processes which are carried out in the field. This include harvest, crop protection, management of weeds/pests, fertilization, planting and tilling. The data is mainly concerned with what kind of seed/fertilizer/chemicals used in the plantation and in which quantity and the manner of their application. Also, it may include chemical composition and texture of the soils, possible existence of pests and weeds in the plantation. Finally, yields are also recorded as the receipts of buyer to whom the product is sold. The most part of the data are recorded from the automatic recording machines with electronic sensors such as satellite digital image sensors, WSNs, soil moisture sensors, automated weather stations on farm, other sensors attached with tractors, quads, harvesters and (semi-)autonomous aerial and grund vehicles. The agricultural Big Data sources and analytic processes are shown in Fig. 1.

Table 2.Big Data Characteristics [10]

Characteristics	Description
Volume (V1)	The size of Big Data ranges from Terabytes to Exabytes and Zettabytes of data and they are increasing exponentially every day.
Velocity (V2)	Big data is growing rapidly. This has to be stored, transmitted and processed rapidly to meet the challenges and demands of the growth and development.
Variety(V3)	In Big Data, there are the variety and heterogeneity of data sources (cloud, web & online computing formats), variables, formats and heterogeneity (unstructured/unstructured).
Veracity(V4)	Big Data faces noise, biases and abnormality in data. Analysis accuracy is subjected to the data veracity.
Valorization(V5)	The ability to propagate knowledge, appreciation and innovation

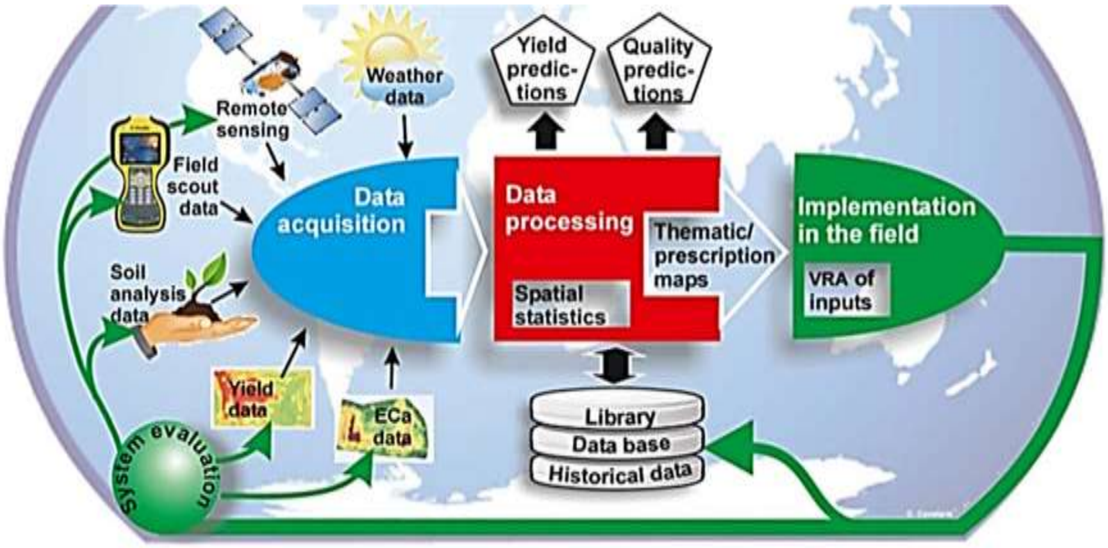

Fig.1. Sources and steps in Agriculture Big Data Analytics[11]

The process of Big Data analytics in agriculture has five major steps [11]:

(i) Data Acquisition and Storage,
(ii) Information Extraction and Cleaning,
(iii) Data Integration,
(iv) Modeling and Analysis,
(v) Interpretation and Deployment.

Big Data technologies analyze is required to deal with video, audio, image and textual data. Correspondingly, to deal with 5V's of Big Data, DL technologies are desirable to fast fitting, optimization and prediction for various decision making in the agriculture scenario. Further, a single central data base will be inadequate to store these data, so parallel storage and processing technologies are needed to be deployed. High computing power (massive storage, faster processers, fast networks, cloud computing and parallel processing), new digital sources of data and higher-level analytics (ML, DL) makes Big Data analytics suitable for generating influential understandings made about complex phenomena and thus agricultural decision making. The farmers can be interacted through the user-friendly visualization tools of Big Data analytic software's with the underlying algorithms, analyze and interpret outcomes of analysis and agricultural decision making for crop protection [4].

4.2 Deep Learning techniques for Crop Protection

Overall productivity of the nation can be increased by ensuring Crop Protection techniques. Crop protection techniques deals with the practices of farmers used to defend their crops against weeds, insects, and diseases. Multiple decisions are made each day by the farmers for protecting their crops from weeds/pests/diseases.The nutrients, water and sunlight are stolen by the weeds from the crops. Also, the impact of various diseases and insects on banana production is devastating.

Globally, AI has already proved its impressive role in agriculture. For instance, Blue River technology based on US has developed DL model which utilize sensors for detecting weeds, type of weeds and the suitable herbicides to apply on the plant. For capturing images, sensors and cameras have utilized. The machine has to learn about different weeds so that the right pesticides in the right quantity can be sprayed as per the area of encroachment. For common man, especially debt-ridden farmers, AI and other emerging technologies are out of reach since it is expensive and lack of knowledge about it. India has wide range of resources, and world's best research institutions. This can be utilized effectively and efficiently for building robust software which has the capability for providing one-time solution for all issues being faced by farmers to assist them in their effort of cultivation. Although there are various approaches exists for the identification of diseases, some recent works are mentioned here.

Lee et al. [12] presented a CNNs system for the automated recognition of plants, based on leaves images. In this paper CNN is trained for learning the feature representations of 44 diverse plant classes, chosen from the Royal Botanic Gardens, Kew, England. Grinblat et al. [13] proposed a simple and powerful NN based on the morphological patterns of leaves' veins for identifying three legume species. Mohanty et al. [14] performed a comparative study of 2 CNN architectures for identifying 26 different diseases of plants, using an open leaf image database of 14 individual plants. The limitation of the study was that the images used are from the laboratory setups, not from the cultivation field with real conditions. Sladojevic et al. [15] proposed another most similar model to detect 13 the plant diseases among 5 plants through the images of the leaves.

Pawara et al. [16] compared CNN with other conventional pattern recognition techniques to identify the plants with three datasets of images of either entire plants and fruits or leaves of the plant and concluded that CNNs outperformed than the other conventional methods. Fuentes et al. [17] proposed a CNN model which can detect 9 diseases on tomato plants and pests on it with adequate performance. Konstantinos P. Ferentinos [18] also proposed a CNN model for identifying plant diseases. the model has been trained using the images of the leaves of diseased and healthy plants and achieved 99.53% success rate. In agricultural research, CNN consistently recognized and classified numerous biotic (fungal and bacterial diseases) and abiotic (deficiency of the nutrients and herbicide injury) stresses [19].

Azree et al. [20] proposed an application that would help rice farmers in detecting Brown PlantHopper(BPH) using deep CNN and image processing. It looked into specific insect pests from the imperfect sticky pad images.Three greenhouse pests such as aphid, thrips and whiteflies counted by Xia et al. [21], using Mahalanobis distance classification watershed segmentation founded on color structures. Li et al. [22] proposed a segmentation model for detecting small sized pests from the surfaces of the leaves. An agricultural robot is used to capture the images of the leaf surface. For segmenting small sizes pests (whitefly) from leaf surface region, multifractal analysis was used, and then classification based on shape and size features is performed on the segmented images.

Yalcin [23] counted moths in pheromone traps with integrated cameras under challenging illumination and environmental conditions using k-nearest neighbour algorithm. Ding and Taylor [24] proposed a 4-layer CNN model for classifying image patches to count the codling moth images taken from the field traps. Espinoza et al. [25] combined CNN with segmentation algorithm for detecting and monitoring of adult-stage thrip and whitefly in greenhouses considering color and morphological features. Ebrahimi et al. [26] proposed a combined SVM classifier and image segmentation method for detecting thrips from the images of strawberry canopy considering color and region features. Garcia et al. [27] developed a distributed grapevine moth detection system using image clustering segmentation and SVM classifier based on gray scale values and gradient in each segment.

Maharlooei et al. [28] proposed a segmentation and classification model for counting soybean aphids of different size on the leaves of a soybean considering their size for classification. Yu et al. [29] proposed a DL model running on embedded device for detecting and counting adult RTB in a pheromone trap with minimal preprocessing. The current researchers are more focused on DL-based crop protection techniques. The recent and relevant DL models focusing on various crop protection areas are summarized in Table 3.

With the emergence of AI and various digitization approaches, crop and soil protection, monitoring, their predictive analysis, and agricultural robotics, become the promising and potential areas in Indian agriculture. For better analysis and processing farmers already has been used data from farm management systems, which are gathered through various sensors and various existing soil samplings. In India agricultural regions has utilized this data along with weather information acquired from satellites has been analyzed with specific algorithms for creating customized AI software's.

Table 3.DL based Crop Protection Models

Paper ID & year	Focused on	Purpose of the model	Techniques used
Esgario et al. [30], 2020	Coffee plant	Biotic stress severity estimation	CNN
Thenmozhi et al.[31], 2019	General	Pest classification	CNN & Transfer Learning
Masayukiet al.[32], 2019	General	Aphid species pest detection	Machine Learning
Arunnehru et al.[33], 2020	General	Disease detection	CNN & Transfer Learning
Gerrit et al.[34], 2019	Potato plant	Virus detection	CNN
Mehmet et al.[35], 2019	Sugar beet	Leaf spot disease detection	CNN
Vimal et al.[36] , 2019	Rice plant	Disease detection	CNN & Transfer Learning
Vishal et al.[37], 2019	General	Disease prediction	CNN
Borja et al.[38], 2020	General	Weed identification	CNN & Transfer Learning
Kun et al.[39], 2020	General	Weed recognition	Graph based DL
Artzai et al. [40], 2019	General	Disease detection	CNN
Sophia et al. [41], 2020	Plantain tree	Disease detection	CNN
Jialin et al. [42], 2019	Turfgrass	Weed detection	CNN
Mosin et al. [43], 2019	Tomato plant	Disease detection	CNN
Hammad et al.[44], 2020	Rice plant	Early disease detection	Region based CNN
Julian et al. [45], 2019	General	Weed detection	Region based CNN
Hamsa et al. [46], 2019	Canola	Weed detection	CNN

5. Conclusion

Overall productivity of the nation can be increased by ensuring proper Crop Protection techniques in plantain tree cultivation. To learn and to perform in depth analysis of the behavioral changes in the sequence of images collected from vast area for a specific period of time, the DL techniques are found suitable. Build, train, and deploy fast, flexible DL model to large scale production will assist the Indian farmers for managing the cultivation of plantain tree by forecasting diseases, weeds and pests and can increase the yields.

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