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Aims and Scope

Technoarete Transactions on Economics and Business Systems(TTEBS) is a peer-reviewed international journal aimed at serving as a forum for intellectual platforms for scientists, academicians, and researchers to disseminate their research findings on the latest development of international Economics and business. The journal aims to cover micro and macroeconomics, health economics international economics, investment strategies for economic development, various empirical studies and various empirical studies and experimental methods pertaining to investment theories, FDI, Banking are also to be covered under the scope of this journal, research related to real estate business insurance services and policies, trade agreement and policies are also welcomed in this journal various, business communication mechanism among difficult cultures human resources management operational management negotiation strategies among different business cultures, political Economics, investigations related to world trade organization and trade organization business are also covered under the scope spectrum of this journal.

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Contents

UX Poker: Estimating the Influence of User Stories on User Experience in Early Stage of Agile Development

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ABSTRACT

Agile methods are used more and more frequently to develop products by reducing development time. Requirements are typically written in user stories or epics. In this paper, a new method called UX Poker is presented. This is a method to estimate the impact of a user story on user experience before development. Thus, there is the opportunity that the product backlog can also be sorted according to the expected UX. To evaluate UX Poker, a case study was conducted with four agile teams. Besides, a workshop followed by a questionnaire was conducted with all four agile teams. The goal of being able to estimate the UX even before development was achieved. Using UX Poker to create another way to sort the product backlog can be considered achieved in this first evaluation. The results show that UX Poker can be implemented in a real- life application. Additionally, during the use of UX Poker, it was found that a shared understanding of UX The participants clarified in the team discussion about UX Poker what related to influence the user stories had on UX and what UX meant for their product.

Keywords Agile, Agile Methods, Usability, User Experience, User Experience Management, UX Management, UX, UX Estimation.

Introduction

Today's users expect to derive a high level of satisfaction while interacting with a product. They also expect to be able to use the product without having to make any major effort to finish their tasks in a quick and efficient manner. Moreover, for a product to succeed, it is important to consider hedonic qualities, that is, the qualities that are not directly target-oriented [1]. It is, therefore no longer sufficient to develop only usable products, they must also inspire the user and address hedonic qualities. In summary, the user wants to have a positive user experience (UX) while interacting with any product or service.

A well-known definition of user experience is given in ISO 9241210 [2]. Here user experience is defined as 'a person's perceptions and responses that result from the use or anticipated use of a product, system or service'. Therefore, user experience is viewed as a holistic concept that includes all types of emotional, cognitive, or physical reactions to the concrete or even only the assumed usage of a product formed before, during, and after use. In ISO 9241-220 [3] the term formed before, during, and after use. In ISO 9241-220 [3] the term human-centred quality has been introduced. Human-centred quality includes user experience, usability, accessibility, and minimizing risks arising from the use.

An additional interpretation defines user experience as a set of distinct quality criteria [1] that includes the classical usability and non-goal directed criteria [4]. Thus, usability is classified as a set of pragmatic factors or qualities, such as efficiency, controllability, or learnability. Non-goal directed criteria are classified as a set of hedonic factors or qualities [4], such as stimulation, novelty, or aesthetics [5]. This definition has the advantage that it splits the general notion of user experience into a number of quality criteria, thereby describing the distinct and relatively well-defined aspects of user experience. This also complies with ISO 9241-220 [3]. One advantage of this definition is that user experience could be measured by using standardized questionnaires such as UEQ+ [6]–[8], SUPR-Q [9], or VisAWI [10]. In addition, a benchmark [11] or KPI [12] can be calculated based on the individual UX factors. The UEQ+ is a modular framework that allows one to combine predefined UX factors to create a concrete UX questionnaire. Currently, the UEQ+ framework contains 20 UX scales, but they can be extended as needed. The construction of the clarity factor can be read as an example [13].

Software development teams use agile methods to develop products or services more and more efficiently. Agile methods (e.g. Scrum [14], Kanban [15], or Extreme Programming (XP) [16]) reduce the time taken to develop a product and make it available on the market [16]. The iterative approach to developing software minimizes the risk of developing software that is not in line with what is needed in the market [17]. The requirements to be developed are collected, evaluated and prioritized in a product backlog [18]. The items with the highest priority were selected for the next development iteration. This also means that the requirements must be prioritized by some method. In agile methodologies, requirements are typically written in user stories or epics.

This paper, we will present UX Poker, a method to estimate the impact of user stories or an epic on user experience. We will also present the results of a first evaluation study conducted in four different companies.

This paper is structured as follows: Section II briefly summarizes the related work. Section III present the research methodology, including the evaluation study. Section IV outlines the results and key findings of our evaluation study. Section V discusses the meaning of the findings, the limitations of our evaluation study, and the improvements that could be made in it. The paper ends with Section VI, with conclusions and ideas for future work.

II. Background and Related Work

In general, requirements are collected and sorted in agile methods in a product backlog. At least that is what the Scrum Guide [13] requires. Also, ISO 9241-210 [2] and ISO 9241-220 [3] recommends a sorted list of requirements. In all cases, it is not defined which criteria would be used for sorting.

In the literature, there are many papers that investigate the integration of UX Methods and Agile development. The range of methods includes usability engineering, user-centred design (UCD) or human-centred design (HCD) [3], and UX methods in general. [19] conducted a systematic mapping study in 2017. The purpose was to investigate artefacts used in communication between Agile methods and user-centred design. A total of 20 artefacts were identified and examined, such as prototype, user story, scenario, sketch, persona, and card, like the design card or the task-case card. During the development iteration, about 56% of the artefacts were used. The rest were used during the discovery or planning phase.

User stories, prototypes (low and high), sketches and mock-ups are the artefacts with which a UX professional can communicate goals or requirements between developer and stakeholder [19], [20]. These artefacts are usually good at representing both UX and functionality [19], [21]. In practice, the items in the product backlog, mostly written as a user story or epic, are sorted by their importance. A user story is typically described according to the following pattern: "As a [persona], I want [some goal] so that [some reason]". The goal of this writing style is to present the requirements shortly and understandably. With "persona" the target group of the user story is named, with "some goal" the actual requirement is named and with "some reason" a justification for the user story is named.

In a product backlog the most important user story is at the top of the list, the least important user story, further down. Here there is no clear definition of what is or is not important. There are different methods to determine the importance. Classically, the product owner decides which items are important based on discussions with the stakeholders. But business or marketing requirements can also influence the importance of a product backlog item. Another possibility could be to include the expected user experience in the sorting.

Choma et al. [22] extended or supplemented the grammar of a user story with user experience aspects and usability requirements. New or replaced components of a UserX Story include personas, goals, interactions, contexts, and feedback. Nielsen's heuristics serve as the acceptance criterion. Expected user experience aspects can be specified as heuristics. Based on these heuristics, the user experience

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UX Poker is a method that aims to estimate the possible impact of a user story or an epic on the user experience, that is produced at the user's site. Before prototypes are created, or the actual development begins, the influence of a user story or an epic on the user experience must be determined. In the end, a user story has been evaluated not only in terms of technical implementation but also in terms of the expected UX. Thus, before the actual development starts, the user stories for the next iteration can be explicitly selected based on the expected UX. For example, if the attractiveness of the product is to be increased, user stories that have a significant expeceted influence on the UX factor attractiveness can be specifically selected.

Besides, the team should adopt the user's perspective through UX Poker. This is to train the team members to look at the development of the product more from the user's perspective. As a general practice, most of the team members are developers. Therefore, they tend to focus more on the technical implementation of the user stories.

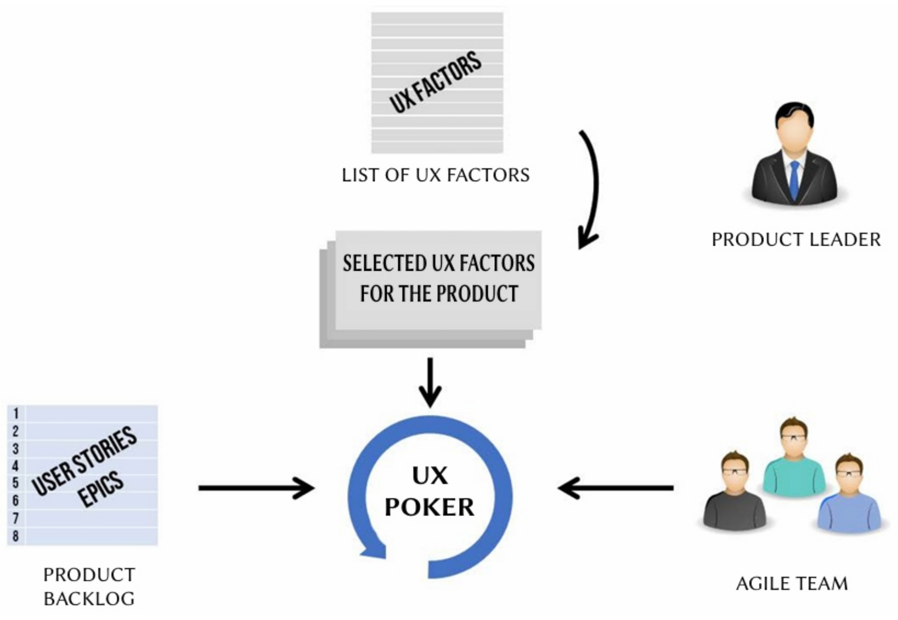

Fig. 1. Procedure of UX Poker with selection of UX factors and UX Poker with product backlog items.

In our opinion, UX Poker makes sense if a product is to be improved in terms of user experience. With UX Poker, a targeted selection of user stories or epics can be made based on the UX estimation before the actual development is made. The goal is to create a basis for a decision about the UX before development starts. If at least a UX estimate of user stories is known before development, the user stories can also be selected specifically.

The procedure of UX Poker is shown in Fig. 1. To use UX Poker, selection of UX factors for a product is necessary, as described in the next section (see 1). UX Poker as a method is described in sections 2 and 3.

1. Selection of UX Factors

To use UX Poker, a selection of UX factors for a product is necessary. As mentioned in the introduction, user experience can be described using UX factors. This allows to description of specific aspects of the user experience in UX factors. These aspects can be, for example, Efficiency (The user can reach their goals with a minimum time required and minimum physical effort), Quality of Content (Subjective impression if the information provided by the product is up to date, well-prepared and interesting), Attractiveness (Overall impression from the product.), or Trust (The product appears trustworthy to the user). The listed examples of factors are certainly not complete. A good overview is provided by Schrepp and Thomaschewski [26] or Hinderks et al. [27].

UX Poker is based on UX factors to describe aspects of user experience and estimate these aspects for user stories or epics. Instead, the introduction of UX Poker must determine which aspects of the user experience are important for the product. For example, trust is certainly a critical UX factor for banking software, but it plays a secondary role in a computer game.

There are different methods to select the important UX factors for a product from a list of UX factors. For example, the method Ranking (sorting UX factors in a team) or Dot Voting [28] (sorting UX factors by prioritizing). Informal consultation between the product owner and a UX professional can also be carried out. In the end, the method used is not decisive. However, no more than 5-7 factors should be selected, or else meaningful estimation of the factors will no longer be attainable. The recommendation for the number of factors is based on the experience of the authors. If the number of factors is too high, there is a risk that UX Poker will become inefficient and therefore the actual goal will not be achieved.

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A. Q1: With UX Poker We Were Able to Talk in a Structured way About the Influence of the Epic on UX

On average, the subjects answered this question with ‘mostly agree’ (median 2), as shown in Fig. 2. The small confidence interval and the low standard deviation related to the small number of participants indicate a homogeneous evaluation, despite there being the four different teams.

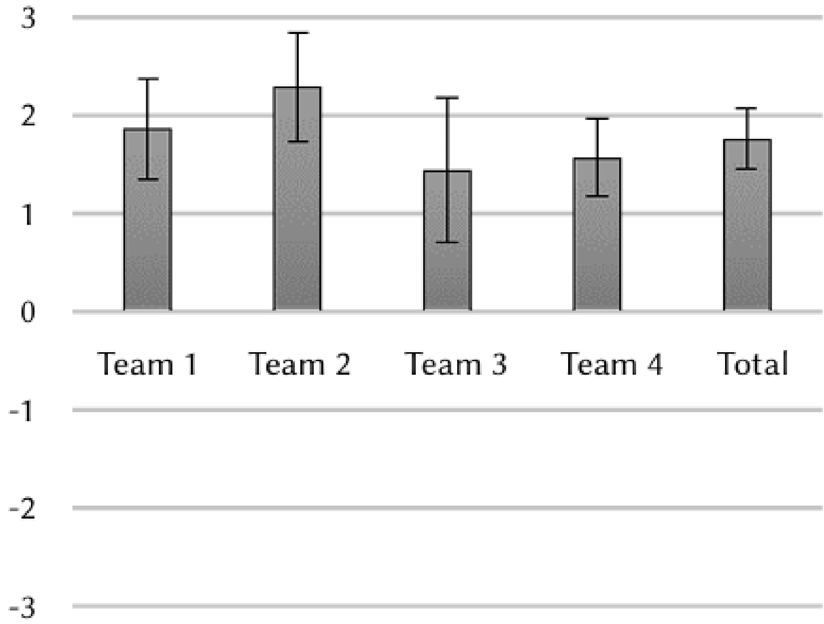

Fig. 2. Result of Question 1 with 95% Confidence Interval as Error Bar.

The total mean value is 1.767 with a variance of 0.737 (Std. Dev.0.858). The Confidence (95%) is 0.307.

B. Q2: UX Poker Helped Me to Get a Better Understanding of the Targeted UX for Our Product.

Team 1 and Team 3 rated the second question as ‘agree’ on average, as shown in Fig. 3. Team 2 and Team 4 tended to rate it as ‘mostly agree’. On average, the overall result is exactly between ‘agree’ and ‘mostly agree’.

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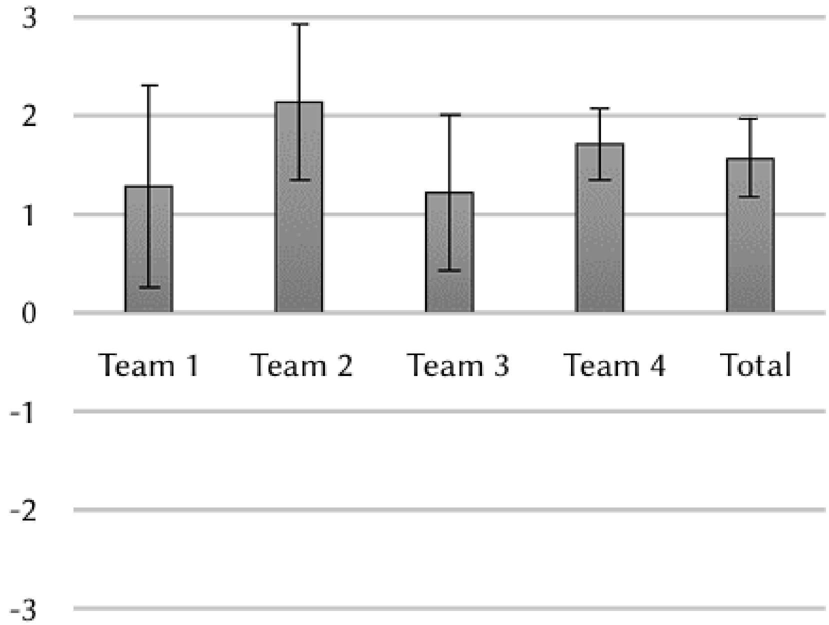

Fig. 3. Result of Question 2 with 95% Confidence Interval as Error Bar.

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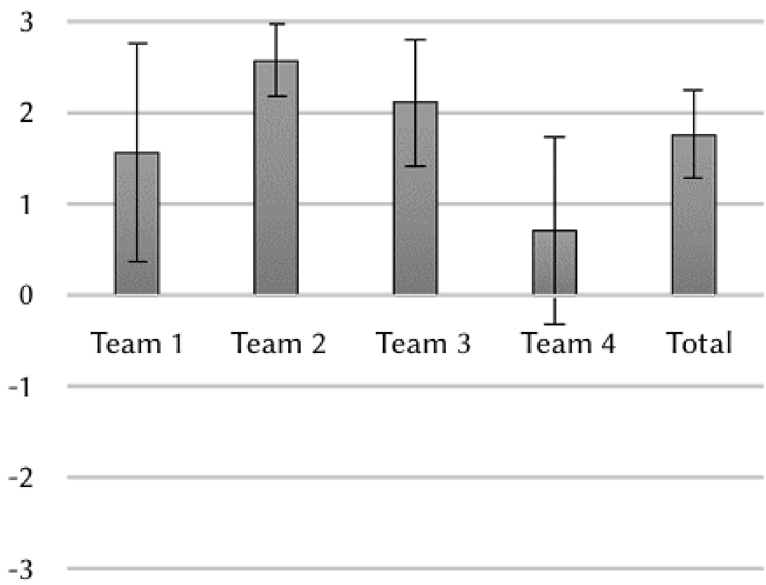

Fig. 4. Result of Question 4 with 95% Confidence Interval as Error Bar.

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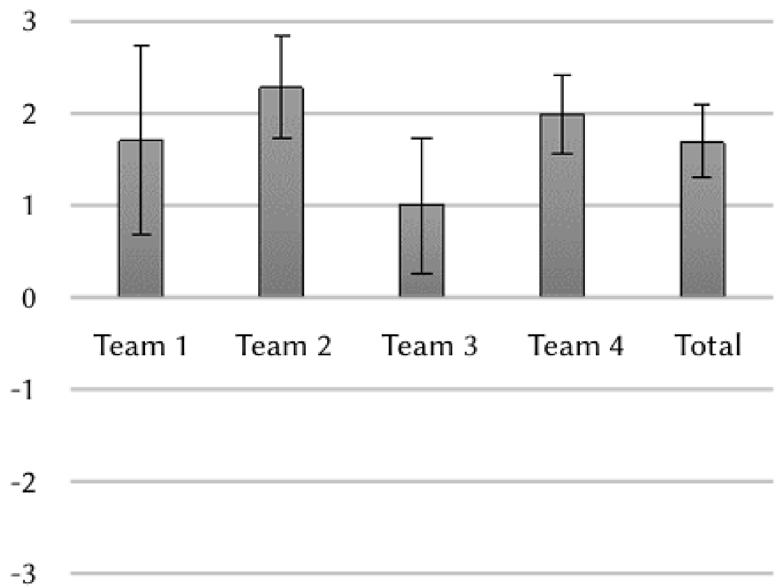

Fig. 5. Result of Question 5 with 95% Confidence Interval as Error Bar.

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V. Discussion

In the results of questions Q1 2, Q2 3, Q4 4 and Q5 5, some differences in the degree of agreement between the individual teams can be seen. We attribute these differences to the different target groups of the teams' products. For example, the target group of Team 1's products is enterprise customers, Team 2's targets are private end customers, Team 3's are craftsmen and private end customers, and Team 4's targets are real estate marketers and private end customers. In addition, the maturity level of the individual teams is different, which would certainly influence the results. However, the tendency is that all results are in the same range when measured against the confidence interval. In the application of UX Poker, new insights have been gained on the use of the method. On the one hand it is the use of the method which is under the consideration of Personas [29]. On the other hand, there is the realization that UX Poker allows a different perspective on epics. We will discuss both points in greater detail in the next sections.

A. The Usage of Personas

In the workshops, a question was repeatedly asked as to which user the UX should be estimated for. It was sometimes not clear to the participants what type of users they should put themselves into the shoes of. The goal of UX Poker is to estimate the UX that will later be created for the user.

For this reason, it makes sense to introduce personas [30] as a prerequisite for UX Poker. Equipped with a clear picture of the personas, UX Poker participants can evaluate the UX from the perspective of these personas. This requirement also coincides with the 'UserX Story' method of Choma et al. [22]. Personas are also a component of this method.

In order to integrate the persona deeply into the development process, it is recommended that persona-driven user stories be used [31]. The user story makes it immediately clear which persona is being addressed.

B. The User Perspective

During the workshops, it became apparent that with UX Poker a different discussion about the implementation of the Epics took place vis-a-vis the exercise in Refinement. Since the participants put themselves into the role of the user, the Epics were analyzed differently. Therefore, things that did not stand out during the Refinement surfaced in the discussion.

For example, a live ticker for a soccer portal app would be implemented. The question that arose out of the discussion was how often the ticker should be updated. The problem was discussed controversially, because the update rate should be quite high when a soccer match was in progress. On the other hand, if no soccer match was being broadcast then a low update rate would be sufficient. In the end, however, everyone agreed that if the refresh rate were implemented 'incorrectly', it would have a negative impact on the UX. If implemented 'correctly', it would impact the UX in a positive way.

The previous example shows that the same Epics, depending on their implementations, can have both a positive and a negative impact on the UX. During Refinement, Epics tend to be evaluated and discussed based on their technical implementation. During the UX poker, the user is in the foreground and it is evaluated from his or her perspective.

C. Limitations

In this study, the use of UX Poker as a method was proposed and evaluated. Whether the estimated UX was actually achieved after development was not evaluated due to the time factor. This needs to be verified in further studies.

Furthermore, the study was only conducted in Germany. International studies should be conducted to exclude cultural and linguistic effects.

VI. Conclusions and Future Work

We have presented a method called 'UX Poker' for estimating the user experience for user stories or epics. The method aims to estimate the UX before implementing the user stories or epics. This has provided another way to sort or filter the Product Backlog in accordance with the estimation. We were able to evaluate this method in an initial study in workshops with 30 participants from four different companies.

The results showed that UX Poker could be used in a real-life application. All participants were able to use UX Poker on concrete examples. It was possible to estimate the possible UX to be achieved for all previously selected UX factors. The use of UX Poker also provided essential insights for the agile team as it took the user's perspective. As best practice, the use of personas in connection with UX Poker has proved to be useful. It helps the participants put themselves into the persona's shoes and assess the UX from the persona's perspective.

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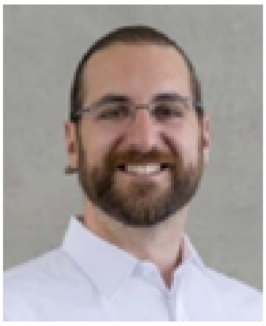

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Her current research interests include the areas of requirement engineering, web system development, modeldriven engineering, early testing and quality assurance. She also collaborates with public companies like the Andalusian Regional Ministry of Culture and Andalusian Health Service in quality assurance issues.

Faster-RCNN Based Deep Learning Model for Pomegranate Diseases Detection and Classification

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A B S T R A C T

India is the largest producer of pomegranates in the world which earns a high profit. However, due to atmospheric conditions such as temperature variations, climate, and heavy rains, pomegranate fruits become infected with various diseases, resulting in agricultural losses. The two most common diseases seen in the Karnataka region are bacterial blight and anthracnose, both of which cause a significant production loss. This paper has detected and classified these two diseases by extracting knowledge from custom trained models using Deep Learning. To overcome the traditional methods, Faster-RCNN helps us to do better object detection.

Keywords
Anthracnose, Deep Learning, Faster-RCNN, Object detection, Tensorflow Bacterial blight.

INTRODUCTION

Asian countries have been manufacturing pomegranates to a larger extent. The exports of pomegranates are growing year by year. Over the past few years, agriculture has swung and is turning into a supply of financial benefit generation. In India, 11.0 lakh tones of pomegranate are produced on 1.5 lakh hectares of land. Maharashtra is India's leading pomegranate producer, India grant 2/3 rd. of the total.

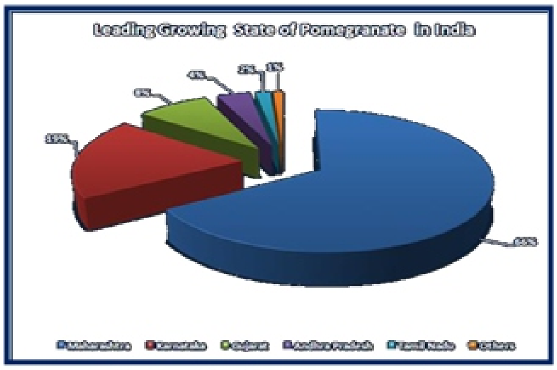

Fig -1: Productivity of Leading Pomegranate Growing States in India.

Importance of Disease Detection in Fruits:

India is an agricultural dependent country as it stands second largest producer of fruits and there is a high demand for quality of fruits in market. The cultivation of fruits faces threat of several diseases caused by pest, micro-organs, weather conditions, soil profile and deficiency of nutrition etc. Which leads to significant reduction in crops when it comes to fruits preservation from diseases diagnosis is very essential to enhance crop production and thus, improve the economic growth [12].

Two Most Common Diseases in Pomegranate Are:
1)Bacterial blight: Dark color irregular spots appear on fruits, and the leaves start dropping, and fruit crack appears in V and L shape and spreads rapidly throughout the farm and cause severe destruction.
2)Anthracnose: it's a kind of that causes irregular brown spots and this disease also leads to severe fruit loss. In the present situation, Farmers in India lack knowledge about how to use pesticides properly; as a result, a proper agriculture system would assist farmers in crop management and decision-making using advanced technology. The intelligent system will detect and diagnose diseases in the fruits for their purpose, and it will restrict the growth of the diseases. Researchers have developed machine learning technology to solve the problems of the farmers [1]. Deep learning is one of the most commonly used subfields of machine learning. It helps in the prediction of various problems and provides solutions [2][3].

LITERATURE SURVEY

One of the important research areas is the automated method for detecting disease-affected fruits, as it offers numerous benefits in terms of fruit preservation. Although lot of research is done in this area, Artificial Intelligence is rarely used for this purpose. To detect multi-fruit classification, the authors proposed a Deep learning approach that uses a faster R-CNN. Fruits such as mango and pitaya are used as ingredients. The dataset was actual data obtained from a farmer during harvest time, and it was divided into two classes for object detection training: mango and pitaya. On the TensorFlow platform, authors used the MobileNet model. In this study, they achieved 99 % accuracy rate [4]. In this paper, using plant leaf photos, the authors propose a deep-learning-based approach for detecting leaf diseases in a variety of plants. They identified and developed deep learning methodologies for good results, and they considered three major detector families: The Faster Region-based Convolutional Neural Network (Faster R-CNN), the Region-based Fully Convolutional Network (R-FCN), and the Single Shot Multibox Detector (SSD). The proposed system capable of identifying various types of diseases and dealing with complex scenarios from within a plant's area [5]. In a deeper analysis using deep learning techniques, Rismayati and Rahari SN [6] investigated CNN's sorting of salak fruits. authors used neural networks to analyze the salak image and classification scheme in a region of interest (RoI). With 3x5x5, they make six filter layers in the first layer. The second layer generates 18 filters size of 6x3x3. The accuracy rate was 81.45%. To solve image classification problems faster, the R-CNN and Quick R CNN methods are used. This method was chosen because it has the highest level of precision in a variety of tests at 1 frame per second (Frame Per Second).

Table -1: Comparison table of various versions of RCNN.

	R-CNN	Fast R-CNN	Faster R-CNN
Time taken for per image	50 seconds	2 seconds	0.2 seconds
Speed up	1x	2x	250x

PROPOSED METHOD

In this article, we propose a system for detecting pomegranate diseases like anthracnose andbacterialblight via TensorFlow for object detection on a Faster R-CNN. on the literature survey, we create our own dataset. For each classifier, i.e., each object label, we collected almost 200-300 images. We used online tool for Image Annotation process where we have uploaded all our dataset, and set the object names (Classifiers) as anthracnose and bacterialblight and used rectangle for creating xml files as annotation directories. After labeling images or Annotations we converted them into CSV (train.csv, test.csv) format because of tensorflow specifications. CSV files are converted into TFrecord format to enhace the training. Once the training has been completed successfully, the protocol buffer(.pb) file is generated with the python inference graph. This graph file can create a user interface on Android or a web application in which a camera is used to detect an object using the trained TensorFlow model.

Convolutional neural network

In [15] CNN's architecture as consisting of an input layer followed by a Conv layer. The dimensions of the conv layer vary depending on the data and problem, so they must be adjusted accordingly. There is an activation layer after the Conv Layer, which is normally ReLU because it produces better performance. A pooling layer is used to minimise the scale after certain Conv and Relu combinations. The flattening layer is used to flatten the input for the completely connected layer after some variation of previously established architecture. The third layer, after the first two, is the output layer.

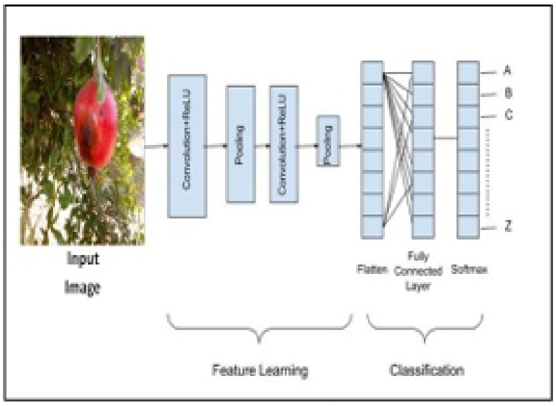

Fig -2: CNN's architecture

Faster Region-Based Convolutional Neural Network (Faster R-CNN)

Faster R-CNN is a Convolutional Neural Network-based object recognition architecture that uses a Region Proposal Network (RPN). It is commonly used in Deep Learning and Computer Vision and is considered one of the most effective object detection architectures.

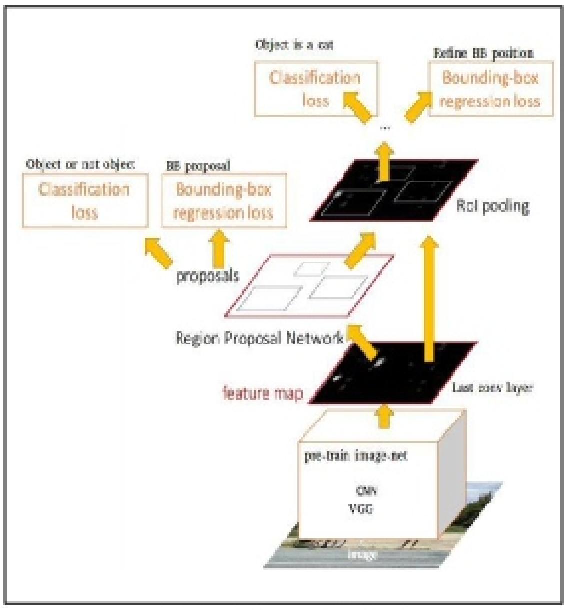

Fig -3: Faster RCNN

It takes an image and sends it to the ConvNet, which creates feature maps for it. Use the Region Proposal Network (RPN) to generate object proposals from these feature maps, and then use the ROI pooling layer to make all of the proposals the same size. Finally, submit these suggestions to a fully linked layer in order to define and predict the bounding boxes of the image.

(Visual Geomerty Group) VGG 16

In [14] It's a 16-layer deep network that's used for feature extraction. We can load a pre-trained version of the network that can be trained on millions of images from the ImageNet database. The network has been pre-trained to classify images into 1000 different object categories.

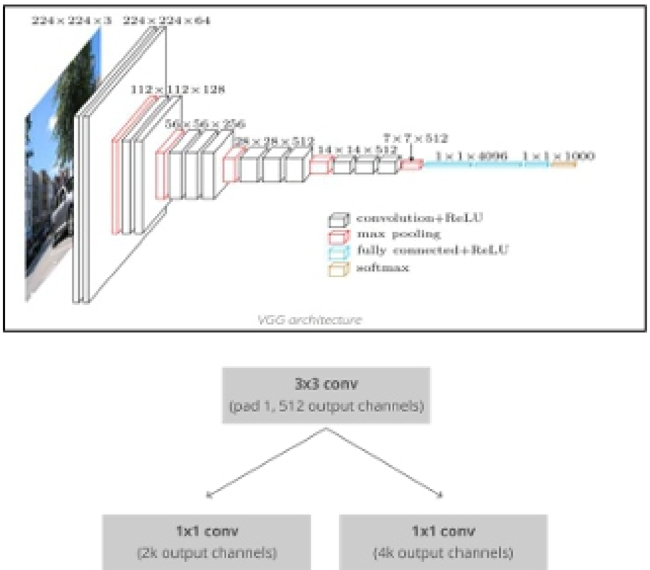

Fig -4: VGG 16 Architecture

VGG16 will eliminate the pre-trained network's bottleneck (classifier) layer. Then, with the exception of the last few convolutional layers, all weights are frozen, and we attach our own classifier with a very low learning rate.

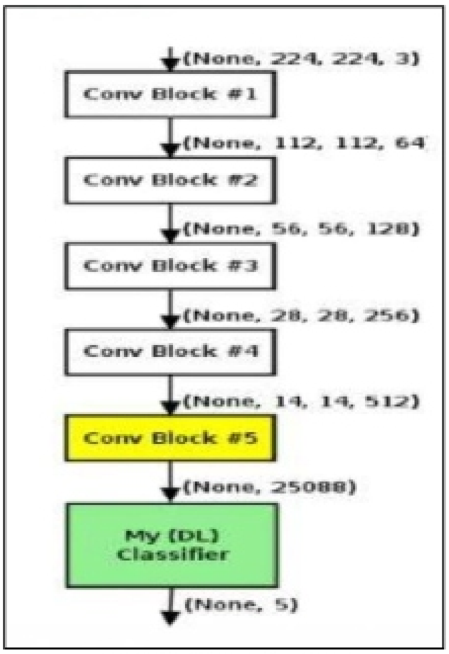

Fig-5: VGG16 Model

regression is the second production, which is used to modify anchors to match the items that are being predicted. The function map, which is convoluted returned by the network as an imput, is used by RPN to implement in a completely convolutional way. With 512 channels and a 3x3 kernel dimension, the convolutional layer is used. Then, using kernel, we'll have two parallel layers of convolution, with the number of channels determined by the number of anchors per point.

We get two performance predictions per anchor for classification. Its score isn't an object (background), but it is an object (foreground).Adjustment layer for regression or bounding box. We generate four predictions: Δxcenter, Δycenter, Δwidth, and Δheight, which we combine with the anchors to form final proposals We have a strong set of object proposals using the final proposal co-ordinates and their "objectness rating."

Anchors

The network generates the maximum number of k- anchor boxes for each sliding window. For each of the different sliding positions in the image, the default value of k=9 (3 scales of (128*128, 256*256, and 512*512) and 3 aspect ratios of (1:1, 1:2, and 2:1) is used. As a result, we get N = W* H* k anchor boxes for a convolution feature map of W * H. These region suggestions were then passed through an intermediate layer with 3*3 convolution and 1 padding, as well as 256 (for ZF) or 512 (for VGG-16) output channels. This layer's output is passed through two 1*1 convolution layers, the classification layer, and the regression layer. The classification layer has 2*N (W * H * (2*k) output parameters, while the regression layer has 4*N (W * H * (4*k) output parameters (denoting the coordinates of bounding boxes) (denoting the probability of object or not object).

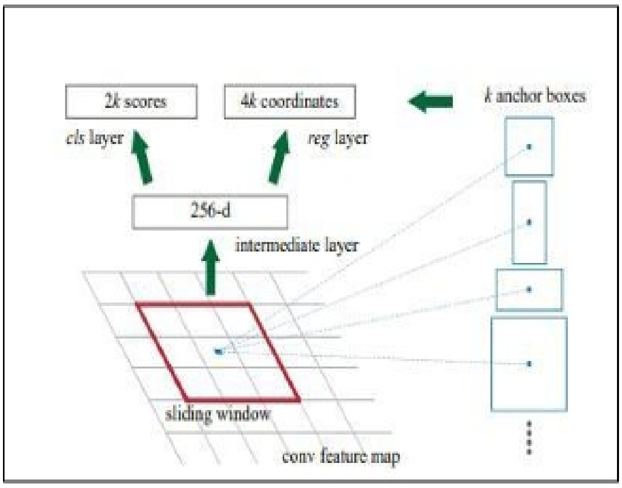

Fig -6 Anchors.

ROI Pooling

Region of interest pooling (also known as RoI pooling) is a popular operation in convolutional neural network object detection tasks. The problem of a fixed image size requirement for an object detection network is solved by ROI pooling. By doing max-pooling on the inputs, ROI pooling creates fixed-size function maps from non-uniform inputs. The number of output channels is equal to the number of input channels for this layer.

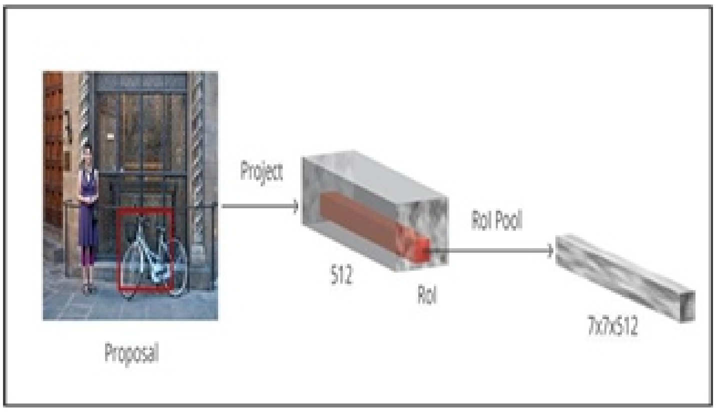

Fig -7 Region of interest pooling

APPROACH

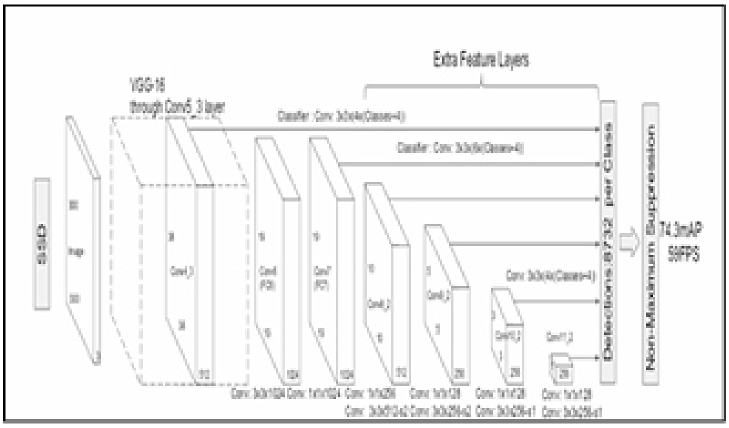

Fig-8: SSD Architecture

This project's network is focused on single-shot detection (SSD). Normally, the SSD begins with a VGG [8] model that has been transformed to a completely convolutional network. Then we add some additional convolutional layers to better manage larger subjects. A 38x38 feature map (conv4 3) is generated by the VGG network. The additional layers result in function maps that are 19x19, 10x10, 5x5, 3x3, and 1x1. As seen in the following diagram, both of these feature maps are used to predict bounding boxes at different scales (later layers are responsible for larger objects).

IMAGE ANNOTATION

PASCAL VOC [9] offers structured image datasets for object type recognition as well as a common collection of resources for accessing the datasets and annotations. Our PASCAL VOC dataset has two classes and a task that is based on it. The PASCAL VOC dataset is well-marked and of good quality, allowing for evaluation and comparison of various approaches. The PASCAL VOC dataset has a smaller amount of data than the ImageNet dataset, making it ideal researchers evaluating network programmes. As shown in the following figure, our dataset is also based on the PASCAL VOC dataset norm.

```xml
<?xml version="1.0"?>
- <annotation>
    <folder>images</folder>
    <filename>3p.jpg</filename>
    <path>images/3p.jpg</path>
  - <source>
      <database>Unknown</database>
    </source>
  - <size>
      <width>300</width>
      <height>168</height>
      <depth>3</depth>
    </size>
    <segmented>0</segmented>
  - <object>
      <name>Bacterialblight</name>
      <pose>Unspecified</pose>
      <truncated>0</truncated>
      <difficult>0</difficult>
    - <bndbox>
        <xmin>55.000003814697266</xmin>
        <ymin>0</ymin>
        <xmax>257.0000305175781</xmax>
        <ymax>167</ymax>
      </bndbox>
    </object>
</annotation>
```


Fig -9 Image Annotation

Fig -10 Labeling Tool

Fig -4: Table example of the labeled dataset.

filename	width	height	class	xmin	ymin	xmax	ymax
1 (1).jpg	1024	974	anthracno	65	55	961	973
1 (10).jpg	300	400	anthracno	72	163	244	357
1 (11).jpg	896	504	anthracno	102	55	725	462
1 (12).jpg	1024	576	anthracno	129	44	855	576
1 (13).jpg	450	300	anthracno	20	52	214	265
1 (13).jpg	450	300	anthracno	214	51	424	240
1 (14).jpg	450	300	anthracno	115	12	420	300
1 (15).jpg	480	360	anthracno	130	43	387	279
1 (16).jpg	800	600	anthracno	194	156	618	547
1 (17).jpg	1300	956	anthracno	4	132	217	424
1 (17).jpg	1300	956	anthracno	221	379	539	757
1 (17).jpg	1300	956	anthracno	509	197	992	749
1 (18).jpg	1280	720	anthracno	45	27	644	683
1 (18).jpg	1280	720	anthracno	553	176	1246	720
1 (18).jpg	1280	720	anthracno	779	9	1280	428
1 (19).jpg	3184	3184	anthracno	347	297	2776	2922

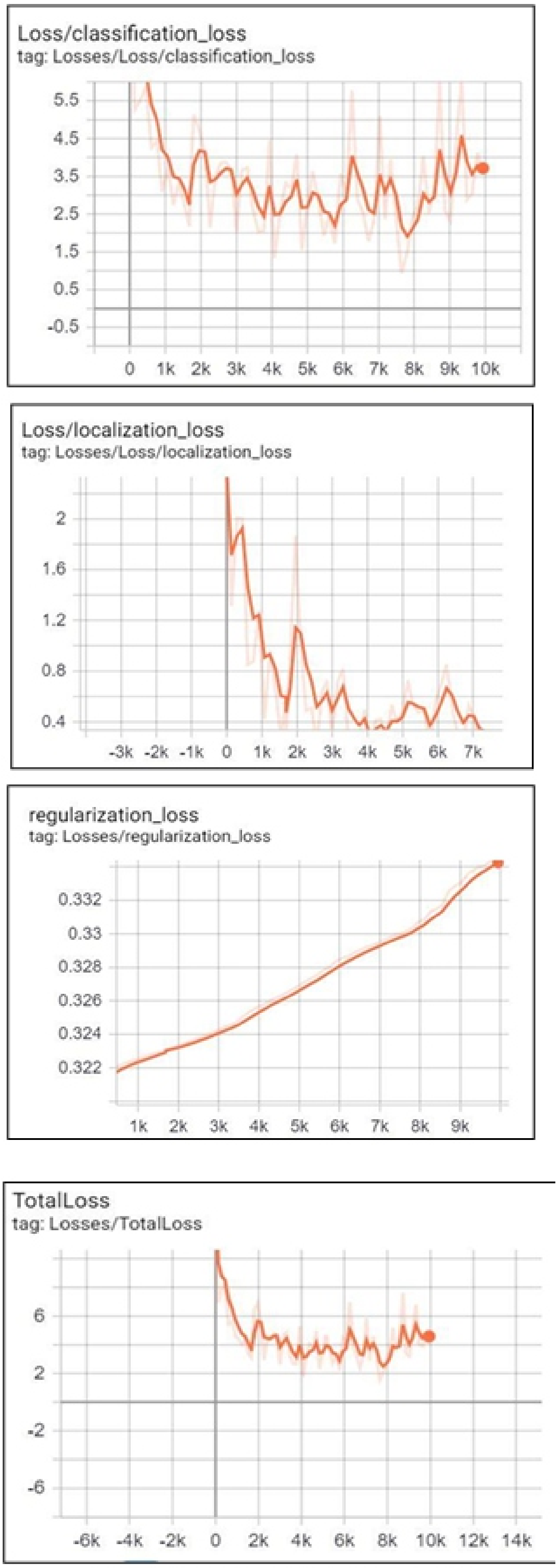

Fig-11: Total Losses of Faster-R-CNN

The number and consistency of the dataset will influence the neural network performance accuracy after the images are trained [10]. Deep learning approaches [11] are growing every day in popularity it enables rapid and efficient solutions, especially in the analysis of large amounts of data. This study used a custom dataset to identify pomegranate diseases such as anthracnose and bacterialblight for deep learning applications. Tensorflow played a major role in this.

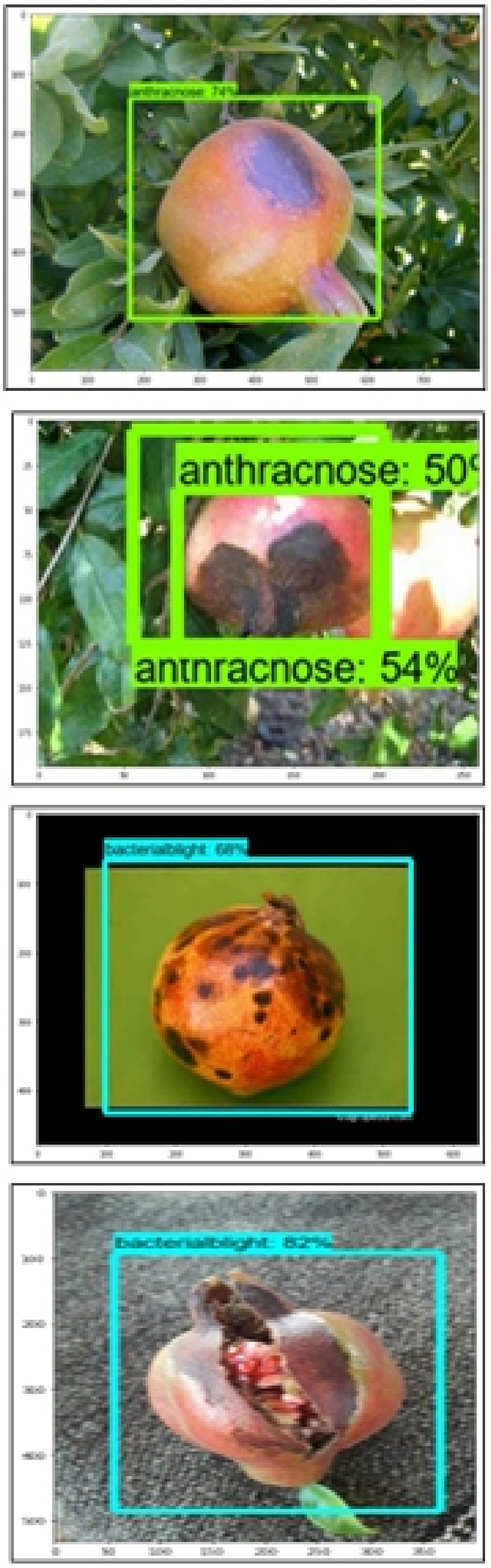

Fig -12: Experimental results.

CONCLUSION

The proposed system is able to detect the diseases in pomegranate and can able to classify them into different categories here we have identified two kinds of diseases anthracnose and bacterialblight . In this study we considered deep learning methodology based on Faster RCNN model which gave an accurate and efficient object detection system. The goal for the future is to figure out how to overcome the issue of low image resolution causing detection failures. Another choice is to apply this approach to crops other than pomegranates.

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Land use Land Cover Study of Sentinel-2A and Landsat-5 Images using NDVI and Supervised Classification Techniques

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ABSTRACT

Land Use Land Cover (LULC) change monitoring plays very significant role in planning, policy making, management programs required for development activities at regional levels of any country. This study is an attempt to monitor LULC change of Vijayapura taluk, Karnataka, India for the period of 25 years from 1995 to 2021 using Remote Sensing (RS) and Geographic Information System (GIS). Satellite Images from Sentinel-2A MSI (Multispectral Imager), Landsat-5TM (Thematic Mapper) are used to generate LULC maps. Vegetation Change in the study area is computed using Normalized Difference Vegetation Index (NDVI) and results show that vegetation rate is increased from 0.6% in 1995 to 27.5% in 2021. Supervised Classification is carried out by using Maximum Likelihood Classification (MLC). 5 major classes considered for classification are namely: Waterbodies, Cropland/Vegetation, Fallow Land, Built-up Area and Barren Land. ArcGIS software tool is used for implementing the proposed study. Google Earth Pro used for accuracy assessment which is done by taking truth values for corresponding Classifications. Results show that the proposed system is able to achieve 88.16% of overall accuracy.

Keywords
High Resolution, Land Use Land Cover, Maximum Likelihood Classification, Multitemporal, Normalized Difference Vegetation Index, Remote Sensing, Satellite Images, Supervised Classification.

INTRODUCTION

While the terms land use and land cover are often used interchangeably, each word has a distinct meaning. The surface layer on the earth, such as trees, urban infrastructure, water, bare soil, and so on, is referred to as land cover. The function of the land, for example, recreation, wildlife habitat, or agriculture, is referred to as land use. When used in conjunction with the term "Land Use Land Cover," it refers to the categorization or classification of human activities and natural elements on the landscape over time using proven empirical and statistical methods of analysis of suitable source materials. [1]. Monitoring land use and land cover change is important for ensuring sustainable development over a period of time, particularly when it leads to inefficient urban development policies and uncontrolled, sometimes anarchic urbanization, which are often linked to environmental threats. [1][2]. Remote sensing techniques are commonly used to identify and track objects or events, as well as to generate detailed charts, records, and statistical data from Earth Observation images in order to provide geo-information to policy makers, experts, and the general public. For this reason, Land Cover Land Use (LCLU) maps are a valuable source of geo-information [3]. Satellite based data is being widely used as a basis for generating valuable information for LULC in various research works [4][5][6][7]. Various techniques of LULC study and change detection have been developed and implemented over the last few decades in India and across the world [8][9][10][11][12] [13] and [14]. In the present study Multitemporal Satellite Images of Landsat-5TM of 30m resolution and high resolution(10m) Sentinel-

2A are used for generating LULC patterns of the study area i.e. Vijayapura taluk situated in Karnataka, India. Vijayapura is characterized by low rain fall, high temperature and very low forest area. Natural vegetation found here is dry deciduous or thorn type of forest and agriculture is the main stay of people [15]. Due to the introduction of ambitious projects from Government of Karnataka like-

- From Water Resources Ministry to Rejuvenate and Replenish Tanks to fill Tanks and there by increase the ground water level [16].
- Working plan of Vijayapuara Forest Division from 2012-13 to 2021-22 [15].

There are noticeable changes in the LULC patterns of study area which makes it more interesting. There has been no attempt made previously to study the LULC in the specified region therefore, the paper aims to utilize geospatial techniques to detect the LULC changes in Vijayapura taluk from 1995 to 2021. Organization of paper: Section I gives the Introduction, Section II briefs about Study Area and Datasets used, Section III and IV explain the Methodology applied to carry out NDVI Calculation and Supervised Classification, Section V discuss the Results, Section VI is the Conclusion.

STUDY AREA AND DATA SET

Study Area

The present study is carried out in Vijayapuara taluk from Karnataka State, India which was earlier called as Bijapur and renamed by Government of Karnataka on 1/11/2014. The latitude and longitude coordinates of Vijayapura are 16015′47.35″ N, 75050′03.47″ E with an area approximately 953.7km2 as shown in Figure 1. Vijayapura is 556m above sea level. The average annual temperature here is 26.5 °C and rainfall is around 718 mm or 28.3 inch per year [17]. Agriculture is the main source of livelihood in the study area and most of the population lies surrounding Vijayapuara city.

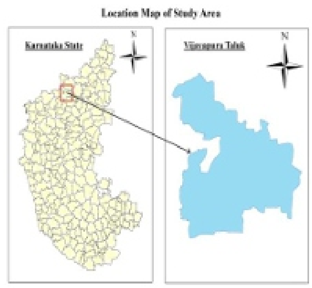

Figure -1: Location map of Vijayapura taluk, Karnataka, India.

Table-1: Details of Satellite Images used in the work.

Sl. No.	Satellite	Resolution and Bands used	Acquisition Dates	Source
1	Sentinel-2A MSI L2A	10m Bands B2, B3, B4, B8	26/01/2021	https://scihub.copernicus.eu/
2	Sentinel-2A MSI L1C	10m Bands B2, B3, B4, B8	24/12/2015	https://scihub.copernicus.eu/
3	Landsat- 5 TM L1TP	30m Bands B1 to B7	31/10/2008 - 145/48 09/12/2008 - 146/48	https://earthexplorer.usgs.gov/
4	Landsat- 5 TM L2SP	30m Bands B1 to B7	13/01/1995 - 145/48 20/01/1995 - 146/48	https://earthexplorer.usgs.gov/

Data Set

Multitemporal high resolution Sentinel-2A MSI imageries composed of 13 bands for the years 2015, 2021 and Landsat-5 TM imageries composed of 7 bands for the years 1995, 2008 are used for LULC mapping of study region. One of the main applications of Sentinel-2A and Landsat composite is for LULC analysis [18]. All Satellite Images used in the study are cloud free or with very less cloud coverage (within 10%) and are downloaded from open-source websites USGS earth explorer and Open Access Hub. Vector data used in the study to get shape file for extracting Region of Interest is downloaded from Karnataka Geographic Information System (KGIS) website. Following table 1 gives the details of Satellite Images used.

SUPERVISED CLASSIFICATION

The aim of image classification is to extract features from remote sensing data by converting it into more concrete categories that reflect surface classes and conditions [19]. For remotely sensed image processing, classification is a commonly used research technique. There are three types of approaches in this collection: supervised, unsupervised, and hybrid.

The supervised classification method requires training samples to define each class. The unsupervised classification approach does not require any additional data because classes are defined solely by spectral value differences. The supervised and unsupervised classification methods are combined in the hybrid classification process [20]. The K-means, parallelepiped, ISODATA, MLC, and minimum distance to means are examples of traditional classification algorithms. MLC is the most precise classification scheme among them [21], as it is known as a reliable and robust classifier with high precision and accuracy. As a result, MLC is the most commonly used pixel-based method for classifying remotely sensed data [22] [23] [24]. MLC is a method for calculating the limit for a given statistic from a specified class of distributions. Electrical engineering can be traced back to the origins of MLC [25].

For the training samples, a normal distribution is assumed. The probability density functions for each group are generated by the algorithm. All unclassified pixels are assigned membership based on the relative likelihood (probability) of that pixel occurring within each category's probability density function during the classification process [26].

The process of classification used in this study is depicted in the following figure 2 Image Mosaicking: As there is no availability of single Satellite Image covering the study area, we have used two Landsat-5TM images of path 145/48 & 146/48 and mosaic them to get Region of Interest (ROI). The method of combining photographs of the same scene into a broad picture is known as image mosaicking. The union of two input images would be the product of the image mosaic process [27].

In the present work ArcGIS geoprocessing tool Mosaic To New Raster is applied on 2 Landsat-5TM images of 1995 and 2008 to get single raster image [28].

Band Composite: Satellite Images are captured in multiple wavelengths of reflected light. We can combine bands of image into picture for better interpretation [29].

Band composite of bands B2, B3, B4 and B8 with 10m resolution of Sentinel-2A images of 2015, 2021 and similarly Composite of bands B1 to B7 with 30m resolution of Landsat-5TM images of 1995, 2008 is performed on the input data set.

Extract ROI: Add vector data to extract ROI from the whole image using shape file. MLC: Five major classes are considered for preparing LULC maps in the study area namely: Water Bodies, Cropland/Vegetation, Fallow Land which is pre-cultivated area, Built-up Area and Barren Land. MLC is applied on the extracted data sets to classify images.

- Training samples are selected for each class. Number of samples selected range from 30 to 100 depending upon particular class and image. For example, 25 to 30 samples for Water Bodies and 90 to 100 samples for Cropland.
- Create signature file and save training samples.
- Perform Maximum Likelihood Classification of input images using signature file.
- Calculate the area covered by each class. Before selecting training samples Google Earth images are investigated carefully.

Accuracy Assessment: Overall accuracy of classified image is done by considering ground truth values from Google Earth Pro and comparing them with the point file created with random values in each class of the classified image.

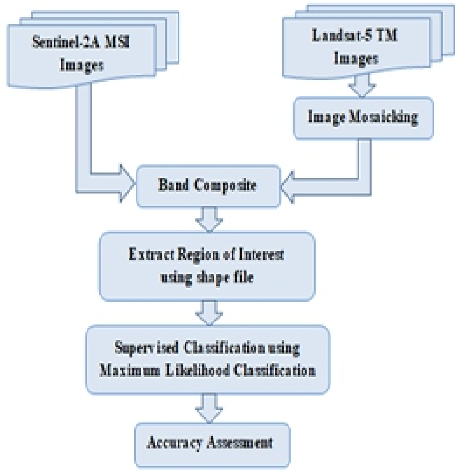

Figure -2: Flowchart of Classification process carried out in the study.

NDVI CALCULATION

The most widely used vegetation index is the normalized difference vegetation index (NDVI), which is a good indicator of large-scale vegetation cover and productivity [30]. The NDVI is a measure of vegetation health based on how plants reflect specific electromagnetic spectrum ranges. A plant appears green to the naked eye because its chlorophyll pigment reflects green waves when absorbing red waves. A stable plant with lots of chlorophyll and cell structures effectively absorbs red light and reflects near-infrared light. A sick plant can do the polar opposite [31]. It's used to improve the presence or absence of vegetation cover by generating the normalized band ratio [32]. The equation to calculate NDVI is defined as

$$NDVI = \frac{NIR - IR}{NIR + IR}$$

NIR stands for Near Infrared, and IR stands for Infrared. NDVI values range from +1 to -1, according to this equation. The non-vegetative surface is represented by negative values, while the green cover is represented by positive values, and the higher the positive values, the denser the green surface [32]. The process of NDVI calculation used in this study is
shown in the figure 3.

- NDVI value for Sentinel-2A images is calculated with bands B4 & B8 using NDVI=(B8-B4)/(B8+B4).
- Similarly, for Landsat-5TM images NDVI is calculated with bands B3 & B4 using NDVI=(B4-B3)/(B4+B3).
- Images are classified into following 4 categories shown in table 2 based on values of NDVI.
- Combination of moderate and high values of vegetation are used to determine the vegetation change from 1995 to 2021.

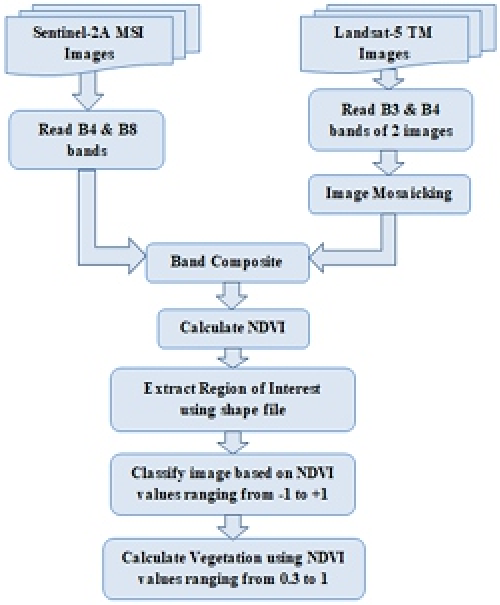

Figure -3: Flowchart for vegetation calculation using NDVI calculation.

Table -2: Vegetation classification with NDVI values.

Sl. No.	NDVI range	Vegetation
1	-1 to 0	Very low
2	0 to 0.3	Low
3	0.3 to 0.6	Moderate
4	0.6 to 1	High

RESULTS AND DISCUSSION

LULC Classification

Land Use Land Cover classification of Vijayapura taluk for multi temporal images of 1995, 2008, 2015 and 2021 covering five major classes namely: Water Bodies, Cropland/Vegetation, Fallow Land, Barren Land and Built-up Area are shown in figure 4. Results from classified maps indicate the spatial distribution of the area occupied by different classes from year 1995 to 2021 and corresponding changes in the LULC patterns which are highlighted with different colors in figure 4. Values for LULC of different classes in terms of area covered in km2 and changes in percentage is represented in table 3. Results show that area covered by Waterbodies is increased from 2.41 km2 in 1995 to 6.82 km2 in 2021 and Built-up Area is increased from 11.6 % in 1995 to 20.03% in 2021. Figure 5 shows the graph indicating visual changes for all 4 years from 1995 to 2021 in all 5 different classes more clearly.

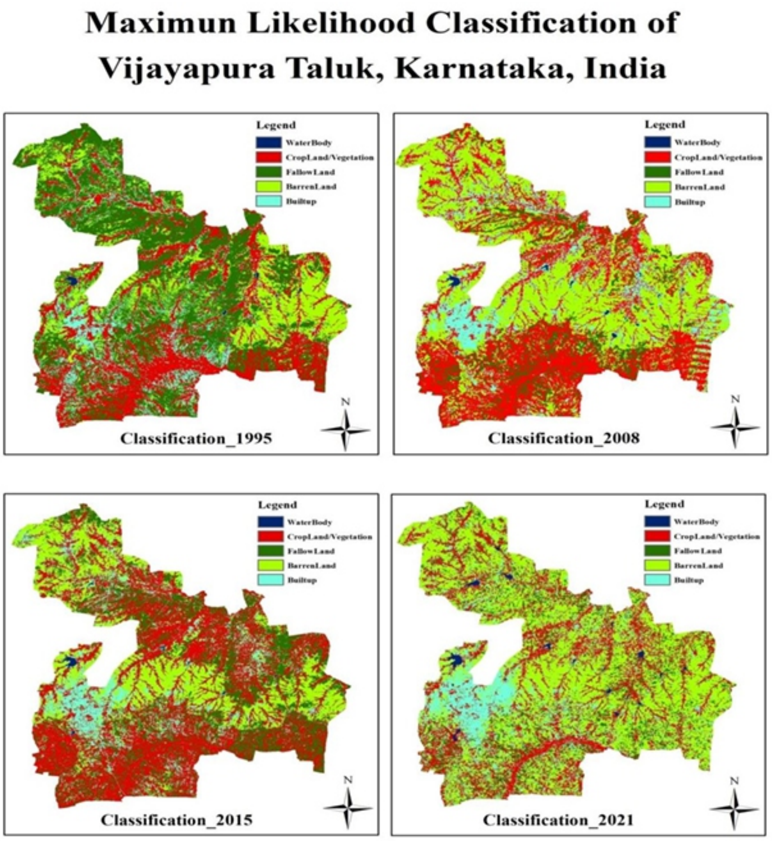

Figure -4: LULC change map for 1995, 2008, 2015 and 2021 of Vijayapura taluk, Karnataka, India.

Table -3: LULC distribution of Vijayapura taluk, Karnataka, India.

Sl. No.	LULC Classes	1995		2008		2015		2021	
		Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
1	Water Bodies	2.41	0.25	3.45	0.36	2.84	0.29	6.82	0.71
2	Cropland/Vegetation	284.13	29.79	360.92	37.84	391.48	41.04	235.79	24.72
3	Fallow Land	386.42	40.51	100.05	10.49	219.14	22.97	114.63	12.01
4	Barren Land	170.15	17.84	349.74	36.67	194.38	20.38	405.4	42.5
5	Built-up Area	110.63	11.6	139.56	14.63	145.89	15.29	191.12	20.03
	Total	953.7	100	953.7	100	953.7	100	953.7	100

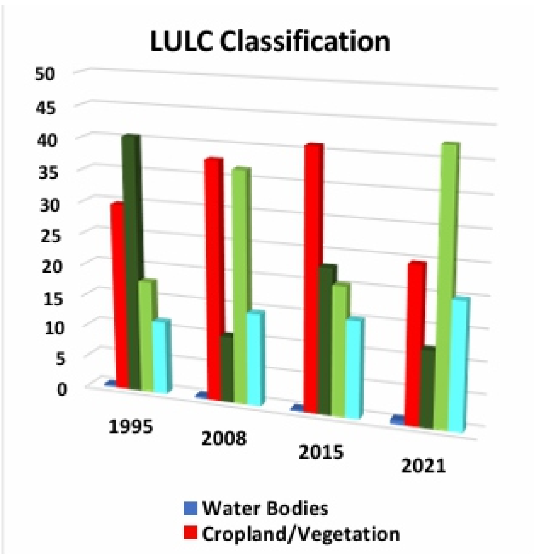

Figure -5: LULC changes during 1995, 2008, 2015 and 2021.

Accuracy Assessment

Accuracy Assessment is done by using error matrix by considering points in the classified image as user values and mapping those points to real time map of Google Earth Pro which are considered as ground truth values and gives producer values. Google Earth is a strong and appealing source of positional data that can be used for research and preliminary studies with sufficient precision and at a low cost. Data availability that allows users from various disciplines to collaborate in order to extract positional data. Google Earth encourage experts to conduct research in order to test and evaluate positional data derived from Google Earth. [32]. Error matrix for overall accuracy of classified images from 1995 to 2021 is represented in the table 4 by considering 245 points which is equal to 88.16%. Table shows that water bodies, Built-up Areas are classified clearly and major misclassified points are from Cropland to Fallow land. Accuracy for individual year is calculated similarly using error matrix and the corresponding values are 85.71% in 1995, 91.8% in 2008, 85% in 2015, 90.16% in 2021 respectively

Table -4: Error Matrix to Calculate Overall Accuracy of classification from 1995 to 2021.

LULC Class	Water Bodies	Crop Land/Vegetation	Fallow Land	Barren Land	Built-up Area	Total (User)
Waterbody	46	0	1	1	0	48
Crop Land	0	39	9	0	0	48
Fallow Land	0	6	41	1	0	48
Barren Land	0	1	3	47	0	51
Built-up Area	0	2	3	2	43	50
Total (Producer)	46	48	57	51	43	245

$$Overall\ Accuracy = \frac{Total\ number\ of\ correctly\ classified\ pixels}{Total\ number\ of\ referance\ pixels} \times 100$$

$$= \frac{216}{245} \times 100 \ = 88.16\%$$

Vegetation Calculation with NDVI

NDVI distribution of study area for the years 1995, 2008, 2015 and 2021 for Very low, Low, Moderate and High vegetation classes is shown in layout figure 7. Corresponding graph representing the comparison of NDVI change is shown in figure 6. Results from classified maps show that there is increase in the vegetation from 0.69% in 1995, 12.15% in 2008, 17.13% in 2015 and 27.52% in 2021.Which means there is 26.83% growth in the vegetation during study period, this growth is shown with the graph in figure 5.

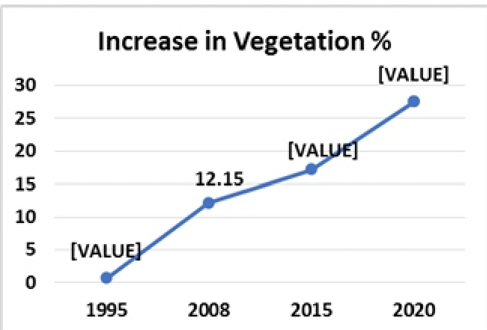

Figure -5: Increase in Vegetation from 1995 to 2021.

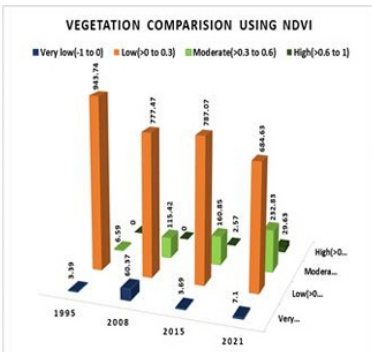

Figure -6: Compariosion of Vegetation Change from 1995 to 2021.

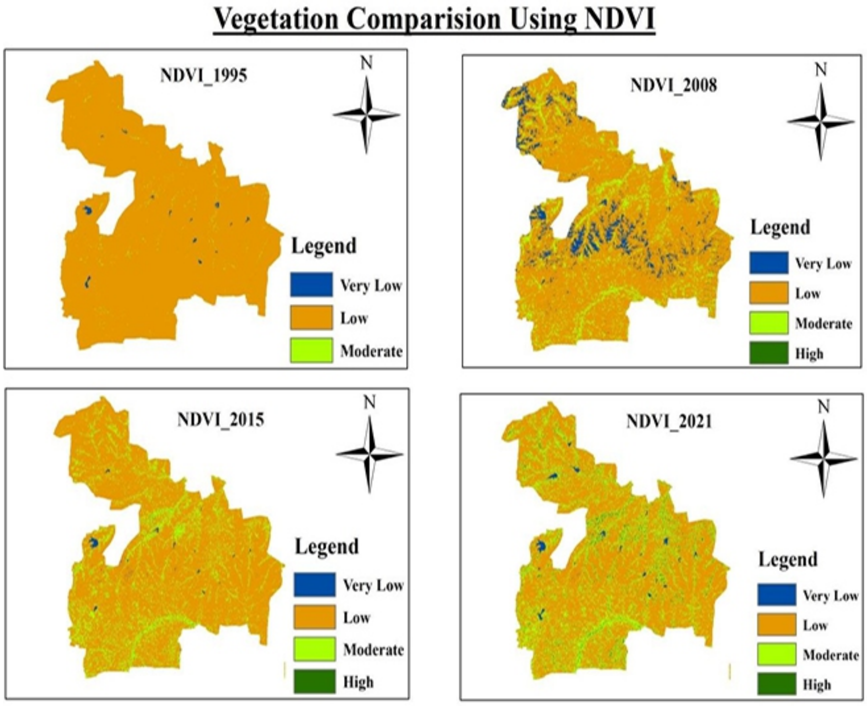

Figure -7: NDVI distribution layout for vegetation of Vijayapura taluk, Karnataka, India for 1995, 2008, 2015 and 2021.

CONCLUSION

The present study is the analysis of LULC change of Vijayapura taluk, Karnataka, India over the period from 1995 to 2021.Work is being carried out using multitemporal high resolution Sentinel-2A and Landsat-5TM images with the help of ArcGIS 10.5 software. Classification is done using pixel-based supervised classification scheme called MLC which is considered to be one of the most accurate, widely used algorithm. Results show that there is increase in Water Bodies from 2.41 km2 to 6.82 km2 due to Water Rejuvenate and Replenish plan, Built-up Area is increased from 11.6% to 20.03% due to urbanization, major area is covered by Cropland and Fallow land 70.3% in 1995, 48.33% in 2008, 64.01% in 2015 and 36.73% in 2021. Barren land is increased from 17.84% to 42.5% in 2021. Vegetation comparison is done using NDVI which shows there is increase in the vegetation from 0.69% in 1995 from 27.52% in 2021. Present study has achieved overall accuracy of 88.16% and as there are no previous works on LULC change done for Vijayapura taluk, results and interpretations of this work are critical for potential Land Use Land Cover practices in the study region. The spatio-temporal analysis is being done by using RS and GIS techniques which is otherwise very tedious work using conventional mapping techniques. The work can be further extended by using unsupervised classification techniques and by using NDVI values and other vegetation indices for classification to achieve more accurate results.

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ANOMALY PATTERN DETECTION IN STREAMING DATA BASED ON THE TRANSFORMATION TO MULTIPLE

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ABSTRACT

Anomaly pattern detection in a data stream aims to detect a time point where outliers begin to occur abnormally. Recently, a method for anomaly pattern detection has been proposed based on binary classification for outliers and statistical tests in the data stream of binary labels of normal or an outlier. It showed that an anomaly pattern can be detected accurately even when outlier detection performance is relatively low. However, since the anomaly pattern detection method is based on the binary classification for outliers, most well-known outlier detection methods, with the output of real-valued outlier scores, can not be used directly. In this paper, we propose an anomaly pattern detection method in a data stream using the transformation to multiple binary-valued data streams from real-valued outlier scores. By using three outlier detection methods, Isolation Forest(IF), Autoencoder-based outlier detection, and Local outlier factor(LOF), the proposed anomaly pattern detection method is tested using artificial and real data sets. The experimental results show that anomaly pattern detection using Isolation Forest gives the best performance.

Keywords: anomaly pattern detection, multiple binary-valued streams, outlier detection, outlier score.

Introduction

An outlier detection method predicts whether a data sample is an outlier [1]. On the other hand, anomaly pattern detection in a data stream aims to find a time point where outliers suddenly begin to occur heavily. A sudden increase of outliers might indicate that an unusual event has happened [2]. The anomaly pattern detection method which was recently proposed in [3] utilizes an outlier detection method that performs the binary classification for outliers. By applying the outlier detection method to each data sample in a data stream, a data stream is transformed into the stream of binary values indicating normal or an outlier for each data sample. Then the occurrence of an anomaly pattern is detected on the stream of binary values by comparing binomial distributions in a reference window and a detection window.

Well-known outlier detection methods such as Isolation Forest(IF) [4], Autoencoder-based outlier detection [5, 6], and Local outlier factor(LOF) [7] compute outlier scores which measure the degree of anomaly in a data sample. Since the anomaly pattern detection method in [3] requires a binary outlier detection method in order to transform a data stream to a stream of binary values, most outlier detection methods, with the output real-valued outlier scores, can not be used directly. Although binary labels of normal or outliers can be obtained by setting a threshold over outlier scores, it is difficult to determine the optimal threshold.

In this paper, we present an anomaly pattern detection method in a data stream based on the transformation into multiple binary-valued data streams. Given a training set of normal data samples, an outlier detection model is constructed using the training set and it is applied to each data sample on a data steam, resulting in a stream of realvalued outlier scores. Multiple thresholds over outlier scores by which abnormal data samples could be distinguished from normal data samples are induced from outlier scores of normal training data samples. By applying the thresholds to a data stream of the real-valued outlier scores, multiple data streams of binary values are obtained. Two approaches for anomaly pattern detection on multiple binary-valued data streams are suggested. The proposed methods, APD-HT/IF, APD-HT/AE, and APD-HT/LOF based on Isolation Forest(IF), autoencoder-based outlier detection, and Local outlier factor(LOF)-based outlier detection methods respectively are tested comparing the performance with the method APD-HT in [3].

The contribution of the paper can be summarized as follows.

– Given normal training data, an anomaly pattern detection method on a data stream is proposed extending the method in [3].

– By setting multiple thresholds from outlier scores of training data samples, an ensemble of anomaly pattern detectors is constructed.

– Well-known outlier detection methods which give the output of outlier scores can be utilized in the proposed method.

The remainder of the paper is organized as follows. In Section 2, the anomaly pattern detection method in [3] is reviewed. In Section 3, we propose a method for anomaly pattern detection in a stream of real-valued outlier scores. Experimental results are given in Section 4 and discussion follows in Section 5.

2 Anomalypattern detection based on binary classification of outliers

While enormous research for outlier detection has been conducted, anomaly pattern detection in a data stream has not been studied extensively [8, 2]. For anomaly pattern detection, in [9, 10], a change in probability distribution on a data stream of real-valued outlier scores was detected based on a one-dimensional Gaussian distribution assumption. In [11, 12], anomaly pattern detection was performed through rule induction on categorical attributes. The method [3] which was published recently showed competent performance for anomaly pattern detection. It detects a burst occurrence of outliers on a binary-valued data stream which is induced by binary classification for outliers.

In [3], given a training set consisting of normal data samples, an outlier detection model is constructed which gives a binary label indicating normal or an outlier for a data sample. A clusteringbased outlier detection method was used for binary outlier prediction. The normal data region in the training set is modeled as a union of hyperspheres by performing k-means clustering on the training data. By partitioning training data to several chunks and applying k-means clustering for each chunk, the ensemble of cluster models can be constructed. Whenatest data sample is not included in the nearest hypersphere in any of the cluster models, it is predicted to be an outlier. By performing outlier prediction for each data sample in a data stream, a data stream is transformed into the stream of binary values where 1 stands for an outlier and 0 for normal.

Two methods for detecting a time point where a sudden burst of outliers occurs were proposed: APD-HT(Anomaly Pattern Detection by Hypothesis Testing) and APD-CC(Anomaly Pattern Detection by Control Charts). Since it was shown that the performance of APD-HT is generally higher than APD-CCin[3],wefocusonthereviewofAPD-HT. In APD-HT, a reference window is set in the beginning part of the binary-valued data stream which is considered as consisting of normal data samples and a detection window is moved forward as a new data sample arrives. Let X and Y be the number of outliers in the reference window and the detection window whose size is m and n respectively. Supposing that the samples in the reference window are generated from the binomial distribution of the proportion p1 and the samples in the detection window are generated from the binomial distribution of the proportion p2, a hypothesis test about the equality of proportions is performed. Under the null hypothesis H0 : p1−p2 =0 and alternative hypothesis H1 : p1−p2 <0,

$$\begin{aligned}
&p\text{-value} = P(Z < z_0),\\
&\text{where } \hat{p}_1 = \frac{X}{m},\ \hat{p}_2 = \frac{Y}{n},\ \hat{p} = (X+Y)/(m+n),\\
&\text{and } z_0 = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}(1-\hat{p})(1/m+1/n)}},
\end{aligned}$$

is computed. For a significance level α, if the pvalue is less than α, then H0 is rejected and anomaly pattern detection is declared. Otherwise, a detection window moves forward for a new hypothesis test.

3 Anomalypattern detection based on the transformation to multiple binary-valued data streams

Binary classification of outliers based on kmeans clustering performs reasonably well and the anomaly detection method in [3] is less affected by the performance of outlier prediction. However, if a well-known outlier detection method can be used, it will improve anomaly pattern detection as well as outlier pattern detection.

Given training data consisting of normal data samples, an outlier detection model is constructed which computes an outlier score of a data sample. From the distribution in outlier scores of training data samples, a threshold for outlier prediction can be induced. However, it is difficult to expect that one threshold value optimally distinguishes outliers from normal data.

Instead of choosing one threshold for outlier prediction, we can use multiple thresholds. For each threshold, the data stream of the real-valued outlier scores is transformed into a stream of binary values indicating outlier prediction with 1 and normal prediction with 0, and the anomaly pattern detection method, APD-HT, is applied in each binaryvalued data stream. Now there are two questions to answer: how to set multiple thresholds, and how to combine the results from APD-HT on multiple binary-valued data streams. In the next subsections, these problems are addressed.

3.1 Howtoset multiple thresholds for outlier prediction

Suppose that outlier scores are small when the anomalous degree of data samples is high, as in the implementation of Isolation Forest algorithm in scikit Learn [13]. Then it is generally expected that the score of outliers is smaller than that of normal data samples. Since a training set contains only normal data samples, thresholds can be chosen using outlier scores of normal training data. We choose the threshold using the percentile numbers in the distribution of outlier scores of normal training data samples. A percentile is a value below which a given percentage of observations in a group of observations falls. When the outlier scores of normal data samples and outliers in a test data set are expected to be separated well, threshold values smaller than 1th-percentile can work well. However, when the outlier scores of normal data samples and outliers in a test set are mixed in a wide range, using too small percentile values as a threshold can not differentiate outliers from normal data samples. In the experiments in Section 4, we test the effects of using various thresholds on the performance of anomaly pattern detection.

3.2 How to combine the results from multiple binary data streams

The anomaly pattern detection method, APDHT, is applied to each binary data stream. A detection window moves forward while the reference window is fixed at the front of the data stream. The distributions in two windows are compared to detect the burst of 1's in the detection window. Hence, a positive or negative prediction is made in each binary data stream and these predictions are combined to make a final decision. We tested two approaches for combining the predictions from multiple binary data streams: All-Agreed and HalfAgreed approaches. In the All-Agreed approach, when the predictions from all the data streams are positive, anomaly pattern detection is declared. On the other hand, in the Half-Agreed approach, when the majority of predictions are positive, anomaly pattern detection is declared. Table 1 summarizes the algorithm of the proposed method.

3.3 Outlier detection methods

Most of outlier detection methods calculate outlier scores which represent the degree at which a data sample deviates from the normal data range. Among various outlier detection methods, we used Isolation Forest and Autoencoder-based outlier detection and Local outlier factor(LOF)-based outlier detection in the experiments of Section 4.

Isolation Forest(IF) [4] is a well-known treebased outlier detection method. Isolation Forest is based on the assumption that outliers are easy to isolate from the remainders of the data. It grows a binary tree by selecting randomly an attribute and a splitting value of the attribute. The process is repeated recursively until all training data samples are isolated at the leaf nodes. The set of isolation trees built on subsets of a training data is called isolation forest. The length of a path where a data sample traverses from the root node to a leaf node is used to compute an outlier score.

Recently, various deep learning-based methods have been used for outlier detection. Autoencoder consists of two components of neural networks. An input data is encoded to low dimensional representation by the first network called an encoder, and it is again decoded to the original dimensional space by the second network called a decoder. Autoencoder is trained so that the error between the reconstructed one and the input data is minimized. Also, the error is used to compute an outlier score.

LOF(Local outlier factor) gives an outlier score based on local density around a data sample [14].

$$LOF(p) = \frac{\frac{1}{k}\sum_{q\in \mathrm{kNN}(p)} lrd(q)}{lrd(p)} \qquad (1)$$

kNN(p) denotes a set of k nearest neighbors of a data sample p. Local reachability density(lrd) of p is computed from the inverse of the average reachability distance to the k nearest neighbors of p. LOF provides an indication of whether p is in a denser or sparser region of the neighborhood than its neighbors [15]

Table 2. Data description

Data	attr.	samples	outlier ratio(%)
Creditcard	28	284,807	0.17
Kdd-Http	3	567,498	0.39
Annthyroid	6	7,200	7.42
Shuttle	9	49,097	7.15
Gaussian	1	102,500	2.44
RBFevents	5	100,000	10.2
Covtype	10	286,048	0.96
Satellite	36	5,100	1.4
Mammography	6	11,183	2.3

4 Experiments

4.1 Experimental Setup

To compare the performance of the proposed anomaly pattern detection method, we used nine data sets including real or artificial data. Detailed description is shown in Table 2. Creditcard data1 is a summary of credit card usage by some card holders in Europe in September 2013. Excluding the attribute indicating usage amount, 28 attributes were used. KDD-http data is a subset of KDD Cup data2, which is composed of data samples whose value of attribute service was http. Three attributes, duration, src-bytes, and dst-bytes, were used as in [16]. Gaussian data is 1-dimensional data where 100,000 normal samples were generated using 5 Gaussian mixture distributions with mean values 0, 1, 2, 3 and 4, and 2,500 abnormal data samples were generated from Gaussian distribution with the mean value 6. RBFevents data was constructed using the artificial streaming data generator RandomRBFevents of MOA [17] with normal data from five normal distributions and outliers from a random uniform distribution.

Other data sets were downloaded from the OpenML data repository. In Annthyroid data, the data samples in two classes, hyperfunction and subnormal functioning, were considered to be outliers. In Shuttle data, data samples of class 1 were treated

DARPA Intrusion Detection Evaluation Program:

Table1. Thealgorithmoftheproposedmethod.

Input: X: a training set of normal data samples
$x_1, x_2, x_3, \cdots$: a test data stream
$\{p_1, p_2, \cdots, p_k\}$: a set of threshold values
Combining strategy: All-Agreed or Half-Agreed
Construct the outlier detection model F by using X.
Apply F for data samples in X and obtain a set of outlier scores G.
Let p_ith-percentile in G be s_i. $(i = 1, \cdots, k)$
Initialize k empty binary streams $B_1, \cdots, B_k$.
for $t = 1, 2, 3, \cdots$
Compute the outlier score for x_t by applying F.
The binary value obtained by the threshold s_i is added to the end of the binary stream B_i for $i = 1, \cdots, k$.
Apply APD-HT on each binary stream B_i $(i = 1, \cdots, k)$, where a reference window is fixed in the beginning part of a data stream and a detection window is set at the end of the stream including the newly arrived instance.
Combine the predictions from all k binary streams by the combining strategy.
if anomaly pattern detection is signaled
Give an alarm for anomaly pattern detection and exit
end if
end for

Table3. Comparisonofanomalypatterndetectionperformance.Thresholdsof0.1th,0.5th,1th,2th,and 3thpercentileswereused.

	APD-HT [3]	APD-HT/IF		APD-HT/AE		APD-HT/LOF	
F1		All	Half	All	Half	All	Half
Creditcard	1	1	0.84	1	0.8	0	0.84
Kdd-Http	1	1	0.79	1	0.8	0	0.02
Annthyroid	0.96	0.96	0.98	1	0.95	1	0.98
Shuttle	0.84	1	0.93	0.6	0.91	1	0.91
Gaussian	1	1	0.9	1	0.88	0.99	0.84
RBFevents	1	1	0.92	1	0.9	1	0.87
Covtype	1	1	0.87	1	0.86	1	0.84
Satellite	0.96	0.98	0.96	1	0.99	1	0.98
Mammo.	0.92	1	0.98	1	0.98	0.04	0.99
mean	0.96	**0.99**	0.91	0.96	0.9	0.67	0.81

	APD-HT [3]	APD-HT/IF		APD-HT/AE		APD-HT/LOF	
Delay		All	Half	All	Half	All	Half
Creditcard	13.2	20.6	15.6	22.8	15.9	-	75.5
Kdd-Http	27.2	15.2	10.8	15.2	10.6	-	11
Annthyroid	72.7	129.6	43.6	15.8	9.4	67.7	32.9
Shuttle	7.6	15.6	9.5	215.9	12.1	15.8	9.4
Gaussian	5.9	17.1	11.1	15.4	9.6	18.8	11.8
RBFevents	5.0	14.7	8.9	14.7	9.6	16.3	10.8
Covtype	134.3	183.8	30.5	15.0	9.8	17.2	12.3
Satellite	21.9	101.3	32.9	14.5	9.4	22.7	15.8
Mammo.	50.0	20.5	14.7	16.1	10.2	210	42.7
mean	37.5	57.6	19.7	38.4	10.7	52.6	24.7

as normal data and data samples in the other classes except class 4 were set as outliers as in [4]. Covtype data targets the prediction of forest cover types from cartographic variables. 10 numeric attributes were used and data samples of class 2 were treated as normal data and data samples of class 4 were set as outliers. In Shuttle data, data samples of class cotton crop and soil with vegetable stubble were used as outliers.

Each data sample is split to a training set which consists of normal data corresponding to 30% of the total data samples and a test set of remaining data samples by which a test data stream is built. In order to simulate the occurrence of an anomaly pattern on a test data stream, outliers were arranged after a sequence of normal data, and the starting point of outliers was set as the actual anomaly pattern occurrence point. An outlier detection model is constructed by the training data and anomaly pattern detection is performed on a test data stream.

The experiment was repeated 100 times by randomly splitting to training and test data. For each test case, when anomaly pattern occurrence is predicted after the actual anomaly pattern occurrence point, it is counted as TP (True Positive) prediction. When an anomaly pattern is predicted before the actual anomaly pattern occurrence point, it is considered FP(False Positive) prediction. If anomaly pattern occurrence is not detected until the end of the test stream, it is marked as FN (False Negative) prediction. In a case of a true positive detection, a distance from the actual anomaly pattern occurrence point to the anomaly pattern prediction point is measured as Delay. After 100 experiments, from the accumulated TP, FP, and FN, the F1 value is computed by Equation 2 along with the average value of Delay.

$$F1 = \frac{2 * precision * recall}{precision + recall}, \qquad (2)$$

$$\text{where } precision = \frac{TP}{TP+FP},\ recall = \frac{TP}{TP+FN}.$$

4.2 Comparison of anomaly pattern detection performance

The performance of the proposed anomaly pattern detection method was compared with the method APD-HT in [3]. APD-HT [3] uses theensemble of k-means clustering for binary outlier prediction. As in [3], the ensemble of three clustering models with the number of clusters 30 was used. The proposed methods, APD-HT/IF, APDHT/AE, and APD-HT/LOF, are based on outlier detection methods of Isolation Forest(IF), Autoencoder(AE), and Local outlier factor(LOF), respectively. For Isolation Forest, the implementation in scikit-learn [13] was used, where the sub-sampling size was the number of training data samples and the ensemble size was 100. The tree height limit H is automatically set by the sub-sampling size ψ as H=ceiling(log2ψ). Outlier scores by Autoencoder and LOF were computed using the implementation in PyODwhich is a Python toolkit for outlier detection [18]. In Autoencoder, 6 hidden layers were set where the number of nodes in an encoder part increased 1.5 times per layer and decreased reversely per layer in a decoder part. Default parameter values in PyOD implementation were used where relu activation function was utilized in all the hidden layers and sigmoid function in the output layer, and Adam optimizer was used. In LOF, the number of neighbors was set to 20 which is a default value in PyOD, and the Euclidean distance metric was used. For Autoencoder and LOF methods, preprocessing of the standard normalization was performed for all the data sets except Gaussian data which is onedimensional data.

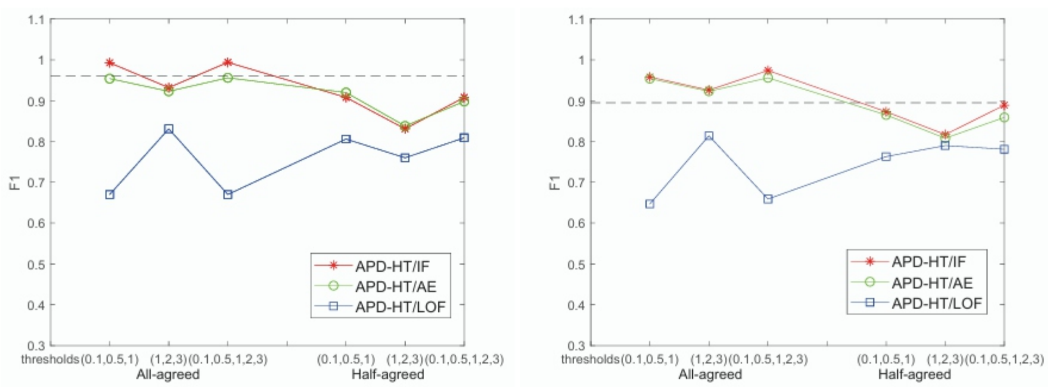
For all compared methods, the size of the reference window and the detection window was set as 400, and the significance level of the hypothesis test was set at 0.01 as in [3]. Five thresholds of 0.1th, 0.5th, 1th, 2th, 3th percentiles were set for the transformation from the stream of outlier scores to binary-valued streams. Table 3 shows the performance of the compared methods in 100 repeated tests by F1 and the average value of Delay. Isolation Forest outlier detection method combined with APD-HT showed the highest F1 value compared with other methods. The all-agreed strategy gave higher F1 value in APD-HT/IF and APDHT/AEthanthehalf-agreed approach, while the average delay is smaller when using the half-agreed approach.

As in [3], we also tested anomaly pattern detection performance in noisy environments. This was simulated by inserting 10% outliers randomly into the normal data sequence and mixing the same

Table4. Comparisonofanomalypatterndetectionperformanceinthesimulationofanoisyenvironment. Thresholdsof0.1th,0.5th,1th,2th,3thpercentileswereusedintheproposedmethods.

	APD-HT [3]	APD-HT/IF		APD-HT/AE		APD-HT/LOF	
F1		All	Half	All	Half	All	Half
Creditcard	1	1	0.85	1	0.84	0	0.85
Kdd-Http	1	0.98	0.86	1	0.77	0	0
Annthyroid	0.95	0.95	0.96	0.99	0.96	1	0.96
Shuttle	0.74	0.96	0.87	0.57	0.82	0.95	0.84
Gaussian	0.84	0.98	0.85	0.97	0.84	1	0.86
RBFevents	0.68	0.91	0.8	0.92	0.8	0.94	0.78
Covtype	1	1	0.83	0.99	0.8	0.99	0.77
Satellite	0.94	0.98	0.98	1	0.98	1	0.98
Mammo.	0.91	1	0.99	1	0.92	0.04	0.98
mean	0.90	**0.97**	0.89	0.94	0.86	0.66	0.78

	APD-HT [3]	APD-HT/IF		APD-HT/AE		APD-HT/LOF	
Delay		All	Half	All	Half	All	Half
Creditcard	14.9	22.2	16.5	27.2	17.8	-	72.8
Kdd-Http	30.5	17.1	11.6	15.9	11.9	-	-
Annthyroid	83.3	138.5	53.3	18.7	15.7	86.6	37.0
Shuttle	12.7	18.7	13.6	377.3	17.6	21.8	15.4
Gaussian	9.3	19	14.5	18.4	13.1	20.7	16.1
RBFevents	15.9	22.2	17.6	20.8	18.0	22.9	17.0
Covtype	135.2	198.2	33.7	16.7	11.5	20.9	14.7
Satellite	27.2	105.6	39.1	16.5	11.3	24.4	18.0
Mammo.	55.5	24.2	17.4	20.1	13.5	233	48.7
mean	42.7	62.9	24.1	59.1	14.5	61.5	30.0



(a)IntheexperimentalsettingofTable3 (b)InthesimulationofanoisyenvironmentofTable4

Figure1. Comparisonofanomalypatterndetectionperformancewhendifferentthresholdvalueswere used.

number of normal data with the outlier data sequence. Table 4 compares the performance in the simulated noisy situations. APD-HT/IF showed the decrease from 0.99 to 0.97 in the F1 value on average compared with the performance in non-noisy situation of Table 3. On the other hand, in APD-HT [3] the decrease from 0.96 to 0.9 in the F1 value was obtained.

4.3 Performance comparison under various threshold values

Figure 1 compares the average F1 values in nine data sets when different threshold values were used in the experimental setting of Table 3 and 4. With All-agreed strategy, APT-HT/IF and APTHT/AE obtained high F1 values when relatively small threshold values such as 0.1th-percentile and 0.5th-percentile were included in the set of thresholds. On the other hand, APT-HT/LOF shows a different behavior pattern with APT-HT/IF and APTHT/AE. It is conjectured that when outlier scores do not well describe the outlier degree of data samples, it is not easy to determine thresholds from the outlier scores of normal training data samples.

5 Discussions

In this paper, we proposed an anomaly detection method in a data stream that utilizes outlier scores by a well-known outlier detection method. When a new data sample arrives, the outlier score for the data sample is computed by the outlier detection model which is constructed from normal training data. Then binary values obtained by applying multiple thresholds for the outlier score are added to the end of the binary-valued data stream corresponding to each threshold. The thresholds are computed from percentile values on the outlier scores of normal training data samples. The binomial distribution in a detection window that moves forward on a binary data stream is compared with the distribution on the reference window at the beginning part of the binary data stream. The predictions made in multiple binary data streams are combined to make a decision for anomaly pattern detection. If anomaly pattern occurrence is detected, an alarm signal is given. Otherwise, the process is repeated for the new incoming data sample.

Among the three outlier detection methods, IF, Autoencoder, and LOF, the anomaly pattern detection using IF, APD-HT/IF, demonstrated the best detection performance on average. It can detect the occurrence of anomalous events by focusing on the pattern where outliers are predicted rather than the accuracy in outlier prediction for an individual data sample. As future work, we intend to apply the proposed anomaly detection method in a real application area such as breakdown detection in production facilities or new topic detection in a social network.

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4. Scientific critique or forum (discussion on a particular scientific topic, based exclusively on management argumentation) and commentaries. Exceptionally, in particular areas, a scientific paper in the Journal can be in a form of a monograph or a critical edition of scientific data (historical, archival, lexicographic, bibliographic, data survey, etc.) which were unknown or hardly accessible for scientific research.

Professional articles:

1. Professional paper (contribution offering experience useful for improvement of professional practice but not necessarily based on scientific methods);
2. Informative contribution (editorial, commentary, etc.);
3. Review (of a book, software, case study, scientific event, etc.)

Language

The article should be in English. The grammar and style of the article should be of good quality. The systematized text should be without abbreviations (except standard ones). All measurements must be in SI units. The sequence of formulae is denoted in Arabic numerals in parentheses on the right-hand side.

Abstract and Summary

An abstract is a concise informative presentation of the article content for fast and accurate Evaluation of its relevance. It is both in the Editorial Office's and the author's best interest for an abstract to contain terms often used for indexing and article search. The abstract describes the purpose of the study and the methods, outlines the findings and state the conclusions. A 100- to 250-Word abstract should be placed between the title and the keywords with the body text to follow. Besides an abstract are advised to have a summary in English, at the end of the article, after the Reference list. The summary should be structured and long up to 1/10 of the article length (it is more extensive than the abstract).

Keywords

Keywords are terms or phrases showing adequately the article content for indexing and search purposes. They should be allocated heaving in mind widely accepted international sources (index, dictionary or thesaurus), such as the Web of Science keyword list for science in general. The higher their usage frequency is the better. Up to 10 keywords immediately follow the abstract and the summary, in respective languages.

Acknowledgements

The name and the number of the project or programmed within which the article was realized is given in a separate note at the bottom of the first page together with the name of the institution which financially supported the project or programmed.

Tables and Illustrations

All the captions should be in the original language as well as in English, together with the texts in illustrations if possible. Tables are typed in the same style as the text and are denoted by numerals at the top. Photographs and drawings, placed appropriately in the text, should be clear, precise and suitable for reproduction. Drawings should be created in Word or Corel.

Citation in the Text

Citation in the text must be uniform. When citing references in the text, use the reference number set in square brackets from the Reference list at the end of the article.

Footnotes

Footnotes are given at the bottom of the page with the text they refer to. They can contain less relevant details, additional explanations or used sources (e.g. scientific material, manuals). They cannot replace the cited literature.
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Note