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Hybrid deep learning – picture fuzzy set model for monitoring human behaviour in forest protection

Deep learning híbrido: modelo de conjunto difuso de imágenes para monitorear el comportamiento humano en la protección forestal

Aprendizado Profundo Híbrido: modelo de conjunto difuso de imagens para monitorar o comportamento humano na proteção florestal

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Abstract

Introduction: This article is a product of the research "Monitoring human behaviour in forest protection" developed at the Hanoi University of Science and Technology in the year 2021,

Objective: This paper presents a new approach using Deep learning, integrated with Picture Fuzzy Set, for a surveillance monitoring system to identify human behaviour in real-time for the pupose of forest protection.

Methodology: The paper has presented a novel approach using deep learning with knowledge graphs to detect humans in large data sets, including finding a human profile. In the proposed model, digital human profiles are collected from conventional databases combined with social networks in real-time, and a knowledge graph is created to represent complex-relational user attributes of human profiles in large data sets. Picture Fuzzy Graphs (PFGs) are applied to quantify the degree of centrality of nodes. The proposed model has been tested with data sets through case studies of a forest.

Results: Experimental results show that the proposed model has been validated on real-world datasets to demonstrate this method's effectiveness. The dataset includes 93,979 identities out of a total of 2,830,146 processed images that identify face detection. In a case study of forest protection in this video, a human is considered to behave normally in the proposed system.

Conclusion: The effectiveness of the theoretical basis for Deep learning, integrated with a graph database, to demonstrate human behaviours by tracking human profiles, for the pupose of forest protection, has been demonstrated.

Originality: The study has presented a new approach using a deep learning model integrated with Picture Fuzzy Sets for the surveillance monitoring system to identify human behaviour in real-time in eco-tourism areas or national forests.

Limitations: This research could be extended by integrating the models of Deep learning with knowledge graphs in reasoning to track in big data.

Keywords: Deep learning, Identifying Human behaviour, Forest Protection, Human Action Recognition.

Resumen

Introducción: este artículo es producto de la investigación "Monitoreo del comportamiento humano en la protección forestal" desarrollada en la Universidad de Ciencia y Tecnología de Hanoi en el 2021.

Objetivo: este artículo presenta un nuevo enfoque utilizando el *deep learning* integrado con un conjunto difuso de imágenes (*Picture Fuzzy Set*), para un sistema de monitoreo de vigilancia para identificar el comportamiento humano en tiempo real con el propósito de proteger bosques.

Metodología: el trabajo tiene un enfoque novedoso que utiliza el *deep learning* con gráficos de conocimiento para detectar humanos en grandes conjuntos de datos, incluida la búsqueda de un perfil humano. En el modelo propuesto, los perfiles humanos digitales se recopilan de bases de datos convencionales combinadas con redes sociales en tiempo real, y se crea un gráfico de conocimiento para representar atributos de usuario relacionales complejos de perfiles humanos en grandes conjuntos de datos. Se aplican *Picture Fuzzy Graphs (*PFG) para cuantificar el grado de centralidad de los nodos. El modelo propuesto ha sido probado con conjuntos de datos a través de estudios de caso de un bosque.

Resultados: Los resultados experimentales muestran que el modelo propuesto ha sido validado en conjuntos de datos del mundo real para demostrar la efectividad de este método. El conjunto de datos incluye 93.979 identidades de un total de 2.830.146 imágenes procesadas que identifican la detección de rostros. En un estudio de caso de protección forestal en video, se considera que un ser humano se comporta normalmente en el sistema propuesto.

Conclusión: se ha demostrado la efectividad de la base teórica para el *deep learning* integrado con una base de datos de gráficos, para demostrar comportamientos humanos mediante el seguimiento de perfiles con el propósito de proteger los bosques.

Originalidad: el estudio presentó un nuevo enfoque utilizando un modelo de *deep learning* integrado con Picture Fuzzy Sets para el sistema de monitoreo de vigilancia con el fin de identificar el comportamiento humano en tiempo real en áreas de ecoturismo y bosques nacionales.

Limitaciones: esta investigación podría extenderse integrando los modelos de *deep learning* con gráficos de conocimiento en el proceso de rastrear en Big Data.

Palabras clave: deep learning, identificación de comportamiento humano, protección forestal, reconocimiento de acción humana.

Resumo

Introdução: Este artigo é produto da pesquisa “Monitoramento do comportamento humano na proteção florestal” desenvolvida na Universidade de Ciência e Tecnologia de Hanói em 2021.

Objetivo: Este artigo apresenta uma nova abordagem usando deep learning integrado a um Picture Fuzzy Set, para um sistema de monitoramento de vigilância para identificar o comportamento humano em tempo real com a finalidade de proteger florestas.

Metodologia: O trabalho tem uma abordagem inovadora que usa deep learning com grafos de conhecimento para detectar humanos em grandes conjuntos de dados, incluindo a busca de um perfil humano. No modelo proposto, perfis humanos digitais são coletados de bancos de dados convencionais combinados com redes sociais em tempo real, e um grafo de conhecimento é criado para representar atributos relacionais complexos de usuários de perfis humanos em grandes conjuntos de dados. Picture Fuzzy Graphs (PFG) são aplicados para quantificar o grau de centralidade dos nós. O modelo proposto foi testado com conjuntos de dados através de estudos de caso de uma floresta.

Resultados: Os resultados experimentais mostram que o modelo proposto foi validado em conjuntos de dados do mundo real para demonstrar a eficácia deste método. O conjunto de dados inclui 93.979 identidades de um total de 2.830.146 imagens processadas identificadas por detecção de rosto. Em um estudo de caso de vídeo de proteção florestal, considera-se que um ser humano se comporta normalmente no sistema proposto.

Conclusão: Demonstrou-se a eficácia da base teórica para aprendizado profundo integrado a um banco de dados gráfico para demonstrar comportamentos humanos por meio do rastreamento de perfis para fins de proteção de florestas.

Originalidade: O estudo apresentou uma nova abordagem utilizando um modelo de aprendizado profundo integrado ao Picture Fuzzy Sets para sistema de monitoramento de vigilância para identificar o comportamento humano em tempo real em áreas de ecoturismo e florestas nacionais.

Limitações: Esta pesquisa pode ser estendida integrando modelos de aprendizado profundo com gráficos de conhecimento no processo de rastreamento de Big Data.

Palavras-chave: aprendizado profundo, identificação do comportamento humano, proteção florestal, reconhecimento da ação humana.

1. INTRODUCTION

Recently, in environmental protection, forests have become significant to the whole world. To identify human behaviour using advanced technology, researchers try to improve applications that monitor human activity in a forest. The ability of humans, via cameras in real-time, is essential to determine the level of human activity. Identifying human behaviour is one of the emerging fields with the rapid advancement of sensing technologies for facilitating analytical operations on human behaviours' as well as acting computer-human interaction. Chi Yuan et. al [1][2] have proposed unmanned aerial vehicles (UAVs) with computer vision-based systems for monitoring and detecting forest fires. In similar research areas, S.Sudhakar et.al [3] have used UAVs to capture colour images using human recognition and smoke monitoring, thereby classifying fire recognition. Furthermore, Luis Merino et. al [4] have proposed fire detection with forest protection monitoring, using infrared and visual cameras to analyse geographic zoning. These techniques are used to monitor forest fire detection using the Voronoi map [5] and its updated information.

To identify positive and negative actions in the studies [6], analysing images collected from human behaviour detection cameras [7] these studies apply deep learning algorithms and the investigation [8] [22] [23] proposed a method of monitoring the behaviour of workers within the framework of vision-based unsafe action detection for behaviour monitoring in motion datasets extracted from videos. Aggarwal et. al [9] have discussed body structure analysis, tracking and recognition with good results. Gavrila [10] has also proposed a taxonomy of 2D approaches, 3D approaches and recognition, detecting the fall event via adaptive boosting algorithm, identifing the human action recognition based on variation in body shape [11]. The studies [10-13, 19] have investigated decision intelligence in context-aware systems to provide a service provision based on an entity's context; an entity has been defined as "a person, place, or physical or computational object" to track a human profile with a reasoning approach.

In this paper, the study has presented a new approach using a deep learning model with an adaptive prioritization mechanism for the surveillance monitoring system to identify human behaviour in real-time in eco-tourism areas or national forests. The proposed model has been tested with data sets through case studies of a forest. The knowledge graph is used to integrate with the proposed deep learning model to identify the person as having a normal or abnormal status in forest protection, as shown in all relations in a graph database.

2. THE PICTURE FUZZY SETS

2.1 Picture fuzzy graph

Definition 1 [20]. A Picture Fuzzy Set (PFS) H on a universe X is an object of the form.

$$H = \{(x, \mu_H(x), \eta_H(x), \nu_H(x)) | x \in X\} \tag{1}$$

where $\mu_H(x) \in [0,1]$ is called the "degree of positive membership of x in H", $\eta_H(x) \in [0,1]$ is called the "degree of neutral membership of x in H" and $\nu_H(x) \in [0,1]$ is called the "degree of negative membership of x in H", and where μ_H, η_H and ν_H satisfy the following condition:

$$(\forall x \in X) \quad (\mu_H(x) + \eta_H(x) + \nu_H(x) \leq 1) \tag{2}$$

and $1-(\mu_H(x)+\eta_H(x)+\nu_H(x))$ could be called the "degree of refusal membership" of x in H. Let $PFS(x)$ denote the set of all the $PFSs$ on a universe X.

Definition 2 [20]. Let $G^* = (V,E)$ be a graph. A pair $G^* = (H,K)$ is defined as a PFG on G^* where $H = (\mu_H, \eta_H, \nu_H)$ is a PFS on V and $K = (\mu_K, \eta_K, \nu_K)$ is a PFS on $E \subseteq V \text{ x } V$ such that for each arc $xy \in E$.

$$\begin{aligned} \mu_K(x,y) &\leq \min(\mu_H(x), \mu_H(y)), \\ \eta_K(x,y) &\leq \min(\eta_H(x), \eta_H(y)), \\ \nu_K(x,y) &\geq \max(\nu_H(x), \nu_H(y)) \end{aligned} \tag{3}$$

The directed PFG can be applied in various sectors where health is a typical example. In the context of the COVID-19 pandemic, PFG can be used to collect information from digital profiles and social networks. A simple example of directed PFG to digital profiles and networks is shown in Fig. 1 as follows.

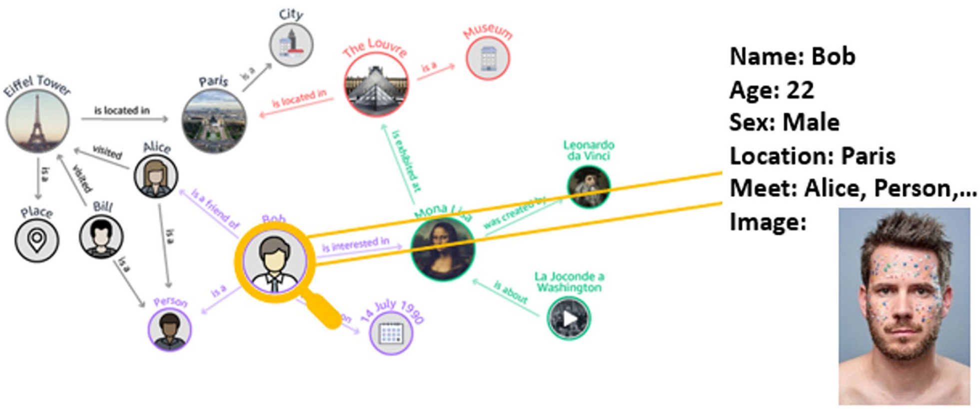

Figure 1. A simple example of directed PFG to digital profiles.
Source: own work

Then, some algorithms are used to create a weighted directed relationship between persons or between person and location, as well as to calculate the distance between PFGs.

Definition 3 [21]. Distances for two PFSs G and H in $X = \{x_1, x_2, ..., x_n\}$ are:
The normalized Hamming distance $d_p\,(G, H)$

$$d_P(G,H) = \frac{1}{n}\sum_{i=1}^{n}(|\mu_G(x_i) - \mu_H(x_i)| + |\eta_G(x_i) - \eta_H(x_i)| + |\nu_G(x_i) - \nu_H(x_i)|) \tag{4}$$

The normalized Euclidean distance $e_p\,(G, H)$

$$e_P(G,H) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}((\mu_i)^2 + (\eta_i)^2 + (\nu_i)^2)} \tag{5}$$

Where: $\mu_i = \mu_G(x_i) - \mu_H(x_i)$, $\eta_i = \eta_G(x_i) - \eta_H(x_i)$, $\nu_i = \nu_G(x_i) - \nu_H(x_i)$.

2.2 Picture fuzzy graph

The knowledge graph or PFG has two kinds including directed and undirected graphs.

Let $G = (V,E)$ be a PFG, where $V = \{v_1, v_2, ..., v_n\}$ represents a non-empty set of nodes or vertices and $E = \begin{pmatrix} e_{11} & \cdots & e_{1n} \\ \vdots & \ddots & \vdots \\ e_{n1} & \cdots & e_{nn} \end{pmatrix}$ denotes a picture fuzzy relation on V. G is considered an undirected PFG if $e_{ij=}\ e_{ij}$, $\forall i,j=1,2,....,n.$. On the contrary, G is considered a directed PFG. For a directed PFG, some degree values on G [11, 21-23] such as the picture fuzzy in degree (d_I), picture fuzzy out-degree (d_o), and picture fuzzy degree centrality (d) can be calculated in Eq. (6), Eq. (7), and Eq. (8) respectively. They are given as follows.

$$d_I(v_i) = \sum_{j=1, j\neq i}^{n} e_{ij} \quad (6)$$

$$d_o(v_i) = \sum_{j=1, j\neq i}^{n} e_{ji} \quad (7)$$

$$d(v_i) = d_I(v_i) \oplus d_o(v_i) \quad (8)$$

3. THE PROPOSED MODEL

The proposed model as shown in Figure 2 consists of 3 main modules of the following:

(1) Face recognition module;
(2) Behaviour monitoring module;
(3) Picture Fuzzy Sets integrated with Deep learning through Knowledge graph representing a graph database containing data about: the person's personal information, photos of a person's face focused on the camera, as well as the history of human behaviour in the resource forest.

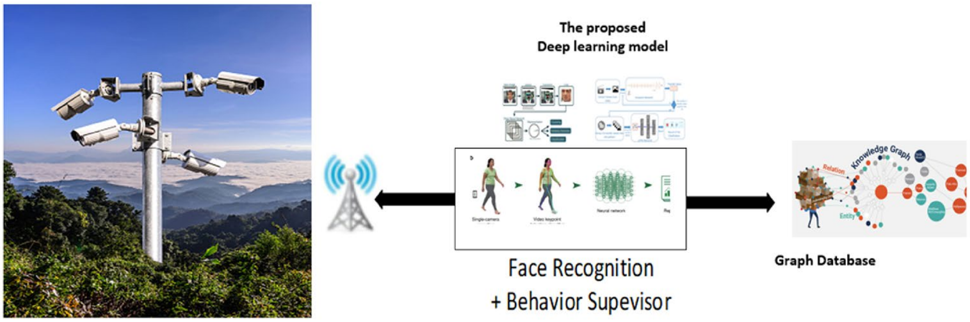

Figure 2. Overview of the proposed surveillance monitoring forest model
Source: own work

In the proposed model, as shown in Figure 1, a video is essentially a series of consecutive pictures. These pictures, grouped in the classification in images of a video, are essentially based on the classification in each image of the video. To solve this problem, two tasks need to be performed: (1) Image processing and sequence-to-sequence classification; (2) Implementation of a model that combine both the Deep learning model with its graph database by tracking human behaviours as well as their activities.

As shown in Figure 1, to capture video online using cameras, we have defined a series of terms of the following elements: actions, activities and behaviours. (1) Actions are descriptions and conscious movements made by humans (e.g., cutting trees, destroying trees... etc.); (2) Activities are several combined actions (e.g., preparing-cutting trees, destroying forests, etc.); (3) Human behaviours describe how the person performs these activities in real-time.

The steps of the proposed model are described as follows. Firstly, videos from a camera have been captured in real-time. These videos are extracted into frames as images so they may be classified. Secondly, a series of images is transformed into a "long short-term memory" (LSTM) Network to give actions as features of a human who has abnormal status in the domain of forest protection. To confirm the ID of the person, the final step involves using a knowledge graph data platform, such as Neo4j, to track human profiles.

4. EXPERIMENTAL RESULTS

4.1 Data sets, experiments and cases study

The proposed model has been tested using the dataset of the Asian celebrity set provided by Deep Glint (source: Trillion Pairs Dataset [14]). The dataset includes 93,979 identities out of a total of 2,830,146 processed images that identify face detection. In a case study of forest protection in this video, the human is behaving normally in the proposed system, so the proposed model has been recognized as a "normal" prediction, as shown in Figure 3.

Figure 3. Face and human recognition model
Source: own work

Figure 4 shows the results of this person's profile tracked in the graph database, in which the red nodes represent his abnormal behaviours.

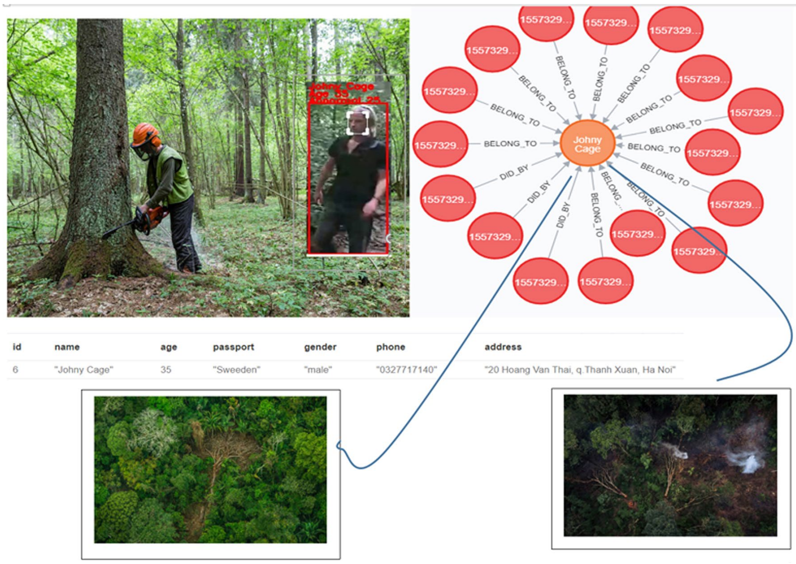

Figure 4. Profile of abnormal behaviour of "Johny Cage" shown in the graph database
Source: own work

In addition, it automatically detected the person with an abnormal behaviour, tracked in the historical profile, stored in the graph database of the system and warned the surveillance system about this person.

4.2 Result Discussions

To validate the proposed model, it has been tested with two methods: BLUFR (Benchmark of Large-scale Unconstrained Face Recognition method), and Behaviour monitoring (Entropy Cross) using cameras taking a series of images in real-time in the forest. The Training data, MS1M-ArcFace, included 85,000 identities / 5.8M images (Data source [14, 15]). The model has been evaluated by using datasets as follows:

- Labeled Faces in the Wild (LFW): 5,749 identities / 13,233 images / 6,000 pairs (source: item [16] references).
- AgeDB-30: 570 identities / 12,240 images / 6,000 pairs. It is a diverse dataset of different ages (source: item [17] references).
- Celebrities in Frontal and Profile (CFP): 500 identities / 7,000 and self-collection: 67 identities / 735 images / 6,360 pairs consist of frontal and profile photos (source: item [18] references).
- CFP-FP: 7,000 pairs. Including 1 frontal photo and one horizontal photo.
- CFP-FF: 7,000 pairs. Includes pairs of frontal photos.

Table 1. Evaluation of Arc Face model

Model	LFW			CFP-FF			CFP-FP			AgeDB-30			Self-collect		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Pre-training	99.77	99.67	0.13	99.79	99.77	0.11	96.2	92.6	0.11	98.25	96.3	0.17	98.65	97.4	0.14
Self-training	99.62	99.43	0.13	99.67	99.23	0.09	93.07	79.83	3.89	95.77	67.4	0.13	98.08	95.56	0.11

Remarks: units%, 1: Accuracy, 2: Validation rate, 3: False accept rate

Experimental results for the proposed model indicate the training model on the Asian photo series inaccuracy in the European and American photo series. However, the accuracy of the Vietnamese photo series is quite good during the experiments.

The evaluation method of the proposed model has been calculated by the percentages of accuracy by dividing the total number of correct predictions by the amount of data. The model loss function used is that of *"categorical cross-entropy"* with the purpose mostly based on the number of data layers. While calculating the value of the loss function, the labels of data for the model training are encoded as *"one-hot encoding"*:

$$y_{onehot} = [y_1, y_2, \dots, y_N] \begin{cases} y_i = 1 \\ y_j = 0 \; \forall j \neq i \end{cases} \tag{9}$$

Where ***i*** is the actual label of data, and ***N*** is the number of data layers.

The output of the softmax function is a vector with ***N*** dimensions representing the probability of a data point that belongs to different layers.

$$y_{predict} = [\hat{y}_1, \hat{y}_2, \dots, \hat{y}_N] \tag{10}$$

The purpose of the categorical cross-entropy is to penalize other predictions that are different from the actual label of the data point. Thus, the "entropy" function gives a percentage of similar two vectors of probability distribution in the same direction as expressed by E.q (11):

$$entropy = -\sum_{i=0}^{N} y_i \log(x_i)\,, x_i \in X, y_i \in Y \tag{11}$$

The entropy value would be large when the two probabilities are considered, as shown in the formula for the *categorical cross-entropy* loss function by summing the entropy values of the given predictions with its one-hot vector as shown in E.q (12):

$$L(y, \hat{y}) = -\sum_{j=0}^{M}\sum_{i=0}^{N} y_{ij} \log(\hat{y}_{ij}) \tag{12}$$

Where ***M*** is the number of data points and ***N*** is the number of data layers. For the "batch gradient" method, ***M*** is the number of data points in the batch, which is equivalent to the batch-size value.

Experiments of the proposed model have been tested using 4,500 data points. The test has been divided by 8:2 into the data set for training and testing. The LSTM model was trained based on a cross-validation strategy. Training data is shuffled and divided into a 9:1 ratio for training and validation. Table 2 provides a comparison of training results for the CNN + LSTM model.

Table 2. Training results of Inception V3

Architect	Train loss	Train Accuracy (%)	Validation loss	Validation Accuracy (%)	Test loss	Test Accuracy (%)
InceptionV3 +3xLSTM(512) +FC(1024) +FC(50)	0.093	96.5	0.13	95.20	0.2	93.2

5. CONCLUSIONS

The paper has proposed a Deep learning model integrated with Picture Fuzzy Sets with an adaptive prioritization mechanism for the surveillance monitoring system to track human behaviour in real-time within a forest domain. The effectiveness of the theoretical basis for Deep learning, integrated with a graph database, to demonstrate human behaviours by tracking human profiles, for the pupose of forest protection, has been demonstrated. In the case study of forest protection by assessing real-time human behaviours, the proposed model proves a novel approach using Deep learning for face recognition with its behavioural surveillance of the human profile integrated with a graph database that can be applied in real-time within a forest protection domain. For further investigation in this study, the models of Deep learning should be integrated with knowledge graphs in reasoning to track groups of human behaviours and relational activities of human groups in real-time.

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