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Using FREAK descriptor to classify plasma influence in Mice sperm

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Abstract

Numerous classification mechanisms anticipate the class's instances to be carried out as the features' vectors, namely the points in a feature's space. It is oftentimes a chance to make an informative exemplification of an image's feature vector for classification problems in computer vision like utilizing global descriptors for the texture description or shape description. The proposed methodology is to classify the sperm image in mice that has been affected through plasma and this methodology consists of three stages. The points of interest could be elicited from sperm plasma images in the first stage by utilizing Adaptive and Generic Corner detector that depended on AGAST (Accelerated Segment Test). FREAK (descriptor of Fast Retina Key-points) was employed in the second stage for describing those points of interest and then computing the standard deviation for those points. KNN (K-Nearest Neighbors) was calculated in the third stage for plasma images classification depending on the STD (standard deviation) amount. The outcomes of the experimental work illustrated that; plasma produced by microwave holds minimum amount of STD than Plasma with high temperature.

Keywords

AGAST, FREAK, Plasma high temperature, KNN, AST

1. Introduction

An image classification in computer vision is a defying action that is achieved with different numerous techniques. Specifically, a scene categorization can rely on the suitable exemplification of an image. In the literature, most works resort to utilizing descriptors that rely on visible information and the recognition of the scenes can be achieved either by relying on the image's objects or the universal information. Global GIST descriptor and Scale Invariant Features Transform (SIFT) descriptor are two of the ultimate methods that have been utilized for scene's categorization. Despite the fact that SIFT was firstly proposed for object recognition, it has been utilized to determine the image's characteristics publicly via utilizing BOW (Bag of Words approach) [1]. The descriptors are quantized to produce a visual-codebook in this approach. The researchers found it more convenient to incorporate information spatially for more enhancing the paradigm of BOW via the descriptors of SIFT. GIST was presented like a descriptor which relies on how can humans perceive a scene. Utilizing universal scene's information may significantly reinforce the classification's outcomes. The descriptor of GIST' is relying on the spatial wrapper that symbolizes the suitable global scene's structure [2]. Recently, it proves that preferable performance may be achieved when the structures can be seen locally and globally with each other in the image [3]. Census Transform Histogram (CENTRIST) descriptor was presented that relies on local binary patterns (LBP) and catches both types of information [4].

An alternate approach was performed to classify an image for human visual system. FREAK was offered as a fast descriptor for the retina key points [5]. The organization of retina is utilizing a circular for the receptive scopes which consist of diverse sizes. Inequality of intensity among receptive scopes pairs may be calculated and more binary classification for the vector is achieved. The receptive scopes intensity was higher for the center of paradigm and conformable to the fovea of a retina. The scopes superposed sampling regions with redundancy which may be added in retina also and might raise the eventual discrimination of the descriptor's power. FREAK can be estimated via matching duty which may offer high object's detection performance. Both the descriptors of BRISK [6] and DAISY [7] can compare the density of the pairs via utilizing a circular manner. When compared to the highly developed descriptors like SIFT, BRISK and SURF, it could surpass them, whilst being straightforward and faster. In modern descriptors similar to CS-FREAK, a fundamental grid could be made simpler via decrementing the receptive scopes' number and the density of the neighborhood could encode reinforcing the matching accuracy [8]. For different work types, FREAK could be utilized to videos actions' recognition via stretching a descriptor by encoding the motion, named Mo-FREAK [9]. Bio-inspired descriptors may be untimely utilized to recognize an object [7]. The DoG filtering imitates the retina's performance that can be applied to classify a texture. This work utilized a modern set of bio-inspired descriptors to categorize the action of a scene. Utilizing FREAK descriptor like a baseline could imitate the retina's kinds [10].

2. Concept of plasma

Plasma is generally a gas which has been ionized and made by the combination of particles' charged electron, molecules and ions. The idiom ionized refers to the presence of one free electron or more free electrons that were not desired by a molecule or an atom. Thermal plasmas or hot plasma have been widely used in medicine to cut, ablate and cauterize tissues through heating; in contrast, non-thermal plasma or cold plasma produces various highly active molecules and atoms without heat. As a result, its effects on the living cells and tissues could be selective and tunable. This makes non-thermal plasma very attractive for medical applications. Hot plasmas or plasmas with high temperature which are depicted via whole kinds (ions, neutral and electrons kinds) were in equilibrium of thermal situation. A type of plasma is called microwave plasma which is in the GHz scope. Microwave produced plasma system can be chosen through other forms of plasma exporter since they have electrode potential with minimal plasma; therefore, the duty of cleaning or replacing the filaments and electrodes was averted. Discharges of a microwave offer cold plasma or non-equilibrium because the electrons could respond to the electric domain's oscillations whereas the ions will not be able to react because of their great mass. Much of the energy produced in the microwave will go to the electrons and yield plasma away from the thermal equilibrium [11].

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3. Proposed methodology

The proposed methodology for plasma images classification has three steps. In the first step, AGAST corner detection is utilized for elicitation of the features of interest from plasma images. The features of interest are described via the descriptor of FREAK in the second step. For the third step, plasma images can be classified via their standard deviations by employing KNN. From the calculations conducted on several images show that the value of STD of sperm images when affected by hot plasma exceeds 30.Therefore; they use the value > 30 to positive classification. The flowchart of the proposed methodology can be illustrated in Fig. 1.

3.1. Employing AGAST to detect image features

An Adaptive and Generic technique for corner revelation relies on the AGAST which should rely on distinctive characteristic scale AST. This approach requires a circle which consists of 16 pixels introducing a discrete circle over a pixel's center. It can match individual pixel's intensity over a circle within the center of pixel (P). If those 16 pixels discovered extra S pixels that are connected over a circle containing intensities which are greater than intensity of P + (threshold) T or the entire of them is less than (P) - (T), then the center of a pixel will be treated as a feature. The threshold (T) may be defined via a user. For this method, a decision optimal tree was built via backward inducement for increasing the velocity. A collection of various decision trees may be trained over more disparate groups of images with particular train [12]. AGAST can be used in a broader way with employing the trees for catering diverse environments. For identifying features process, templates can play a fundamental role. Those templates forms are chosen for determining corners due to the fact that isotropy enjoys the characteristic of being a promising quality

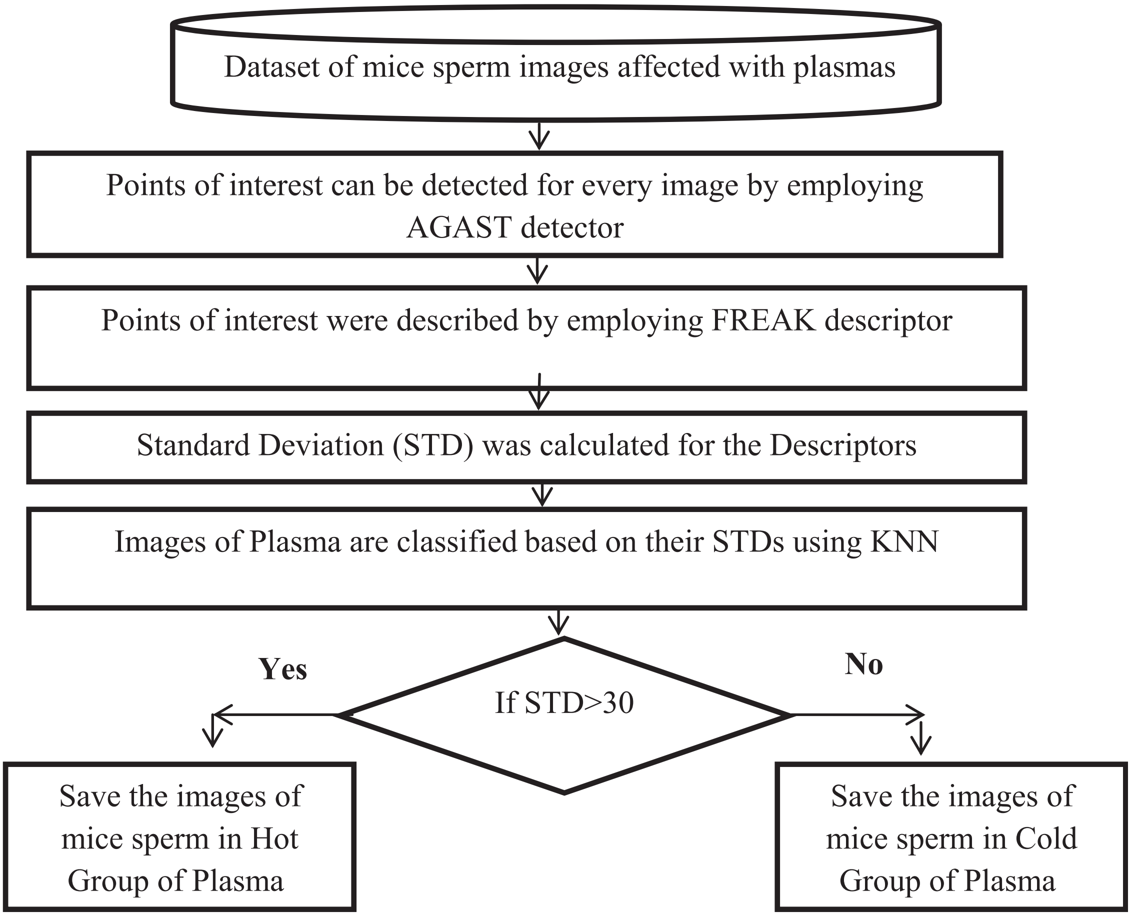


Fig. 1. Flowchart of the proposed methodology for classifying plasma images.

of circular templates. For a preferable accuracy achievement, the pixel's intensity at sub-pixel grade may be necessarily calculated via interpolation. An AGAST which is applied must rely on a particular data set that included entire potential combinations of 16 pixels over the circle that makes it certain that the decision tree can perform its work under all circumstances. AGAST introduces an algorithm of a tree switching which alters the resolve trees automatically. It is possible to employ one of those trees over homogeneous domains and the other could be employed over heterogeneous domains. Accomplishment of an AGAST rises for casual scenes. Combing those two growing approaches makes an AGAST able to work in every arbitrary ambience without any stage of training as illustrated in Fig. 2 [13].

3.2. Employing FREAK to describe image features

The FREAK is regarded as a dual descriptor that has been calculated depending on the brightness comparison produced tests for a quantity of sampling placement over a key point [14]. FREAK can consist of the following steps: -

3.2.1. Sampling pattern

The sampling pattern adopted via the descriptor of FREAK is inspired biologically via retinal manner in the eye. So, the points' sample constituting the basis for calculating the descriptor of FREAK is arranged in a sample manner as illustrated in Fig. 3.

N points sample existing all over the specific key point have been smoothed via a Gaussian kernel before

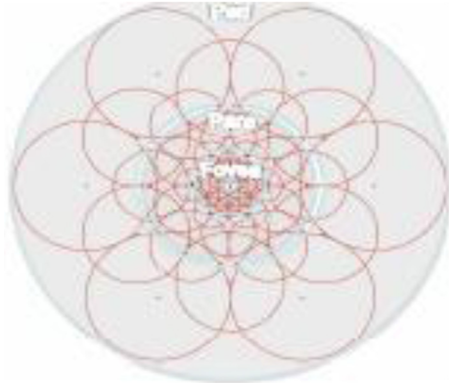


Fig. 3. FREAK sampling pattern. Red circles have represented the standard deviations for the kernels of Gaussian that were computed for the corresponding points sampling. 43 points sampling totally has been chosen for the descriptor of FREAK sampling manner [14].

calculating the descriptor. Now, the kernel's size is diverse with regard to the sampling point's location for simulating a retina behavior of humans identical to the visual system for humans. FREAK descriptor sampling points, hence, illustrate the receptive fields' centers [10].

This can be illustrated by Eq. (1) [14].

$$P_i = P(x_i, y_i) = L_{ri}(x_i, y_i) \tag{1}$$

3.2.2. Descriptor building

The descriptor of FREAK is constructed depending on intensity comparisons between various pairs of sampling points which have been smoothed such as

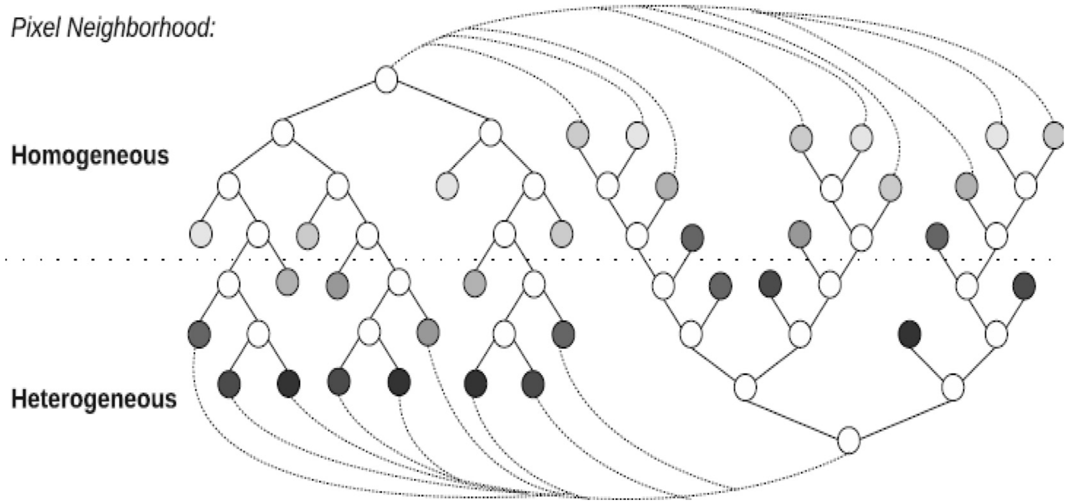


Fig. 2. AGAST's basic concept states that it is possible to shift from two or more specialized trees instantly with the change of the pixel neighborhood. As much as the gray of a leaf turns light, more equal pixels are found in the configuration [13].

receptive fields' centers which can be defined by Eq. (2) [15].

$$S(P_a) = \begin{cases} 1, & \text{if } P_i > P_j \\ 0, & otherwise \end{cases} \quad (2)$$

The FREAK sampling manner makes it possible to have numerous pair wise comparisons which will result in a huge descriptor. Since a great number of the pairs may not succeed in proving their usefulness in giving an account of an image's content, the researchers implemented an algorithm of training, and the manner of sampling can be illustrated in Fig. 3 for identifying beneficial pairs for descriptor building. The trained shape of the descriptor of FREAK can define 512 [15]. Pairs of the sampling required to be examined for computing the bit-string can be explained in Eq. (3). Fig. 4 illustrates the picked 512 sampling point pairs that have been classified into four clusters; each cluster has 128 pairs. A symmetric pattern can be taken in these clusters because of the pattern orientation over the global gradient. When using a different value of FREAK pairs than 512, the classification results do not change, but the numbers or descriptors are increased or decreased (see Fig. 5).

3.2.3. Orientation normalization

FREAK descriptor's orientation can be evaluated using 45 picked sampling pairs which are symmetrically ordered with regard to the sampling pattern's center as shown in Fig. (3). The orientation o for a given key-point can be calculated in Eq. (3) [15].

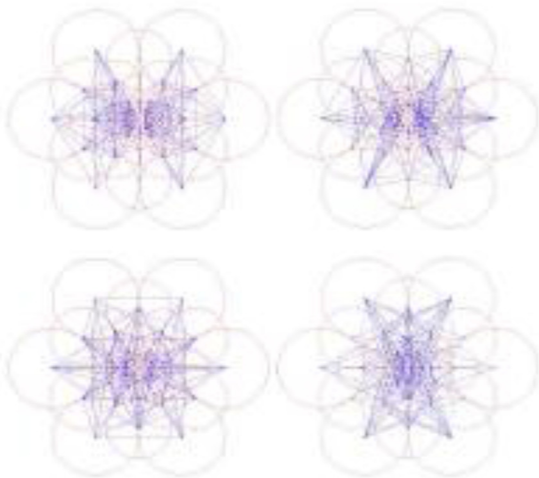


Fig. 4. Explaining four binary experiments clusters that compose FREAK. Peripheral receptive domains (top left), and central (bottom right) [15].

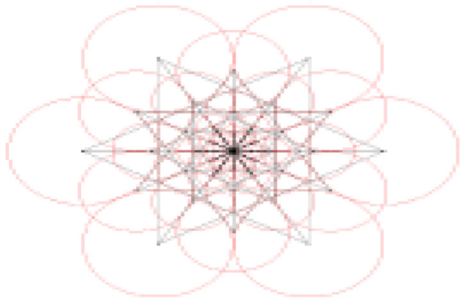


Fig. 5. Pairs can be selected to calculate the key-point orientation [15].

$$O = \frac{1}{M} \sum_{P_i, P_j \in G, i \neq j} (P_i - P_j) \frac{T(P_i) - T(P_j)}{\|T(p_i) - T(P_j)\|} \quad (3)$$

After the elicitation of the descriptors of an image, the Manhattan of those descriptors can be calculated via Eq. (4). The Manhattan distance between two components can be calculated by the summation of differences of their identical elements. The distance formula among the points A= (a1, a2, etc.) within the points B= (b1, b2, etc.) can be calculated via Eq. (6) [16].

$$d = \sum_{i=0}^{n} a_i - b_i \quad (4)$$

Standard deviation for descriptors is elicited from an image through Eq. (5) [16].

$$STD = \sqrt{\sum_{gry=0}^{Level-1} \left((gry - mean)^2 * pro(gry) \right)} \quad (5)$$

Details of the equations were omitted to reduce the number of sub-symbols and just citing the reference of the original equation.

3.3. Classification of features using KNN

KNN is a learning method which can keep entire training data for classification. Presenting a lazy learning method can prevent it from being used in abundant applications like dynamic web mining for a major great repository. A single enhancing efficiency way was discovering some representatives in order to represent the whole training data to be ranked; a paradigm must be built for learning via induction of the dataset which is trained, and utilizing this representative to rank. Various approaches existed like decision trees or neural networks which were initially designed to construct a paradigm like this. Performance is one of the assessment scales for diverse approaches. KNN was a straightforward classification way but efficient. It may be convenient as a maximum effective approach on corpus of Reuters newswire for stories to categorize the text. It motivates us for constructing a paradigm to reinforce the efficiency of KNN while preserving the accuracy of its ranking as well [17].

The main steps of KNN technique can be summarized as:

1. Specifying a positive integer k over a neoteric sample
2. K entrances are selected from the dataset which is closest to a neoteric sample
3. Finding a drastic common entry ranking.
4. For this ranking, the neoteric sample is given to a training dataset shown in Fig. 6, which contained 36 points of data that included 2 classes represented by circles and squares and may distribute in 2-dimensional space of data.

3.4. Suggested algorithm

A suggested algorithm can be offered like:

Input: - Images of mice sperm affected with Plasmas

Output: - Classify the type of plasma that affected sperm in mice

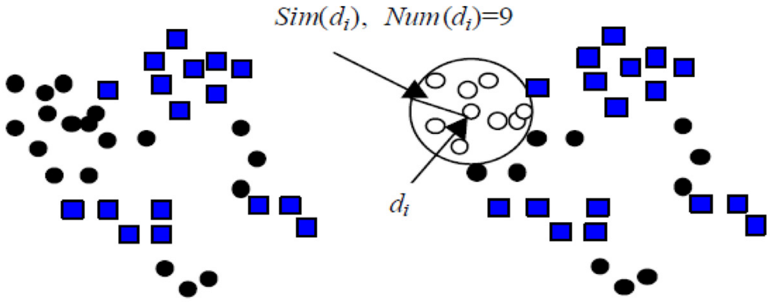
```
begin
    Step-1: For k=1 to   count of images.
        Step-2: acquire Imags[k]
        Step-3:  Points of interest are detected for all (Images[k]) by employing
                 detector of AGFAST for corner and save the outcomes in (AG_Imags[k])
        Step-4:  Points of interest are described to all (AG_Imags[k]) by employing
                 descriptor of FREAK.
        Step-5: Calculate the standard deviation (STD[k]) to whole descriptors by
                 employing Eq. (1)
        Step-6: Images can be classified relying on their STD[k] by utilizing classifier of
                 KNN
                 If (STD[k]<30) Then save Imags[k] at cold plasma group
                      Else
                 save Imags[k] at hot  plasma group
             End //for If statement

    End // for loop for k

End.
```

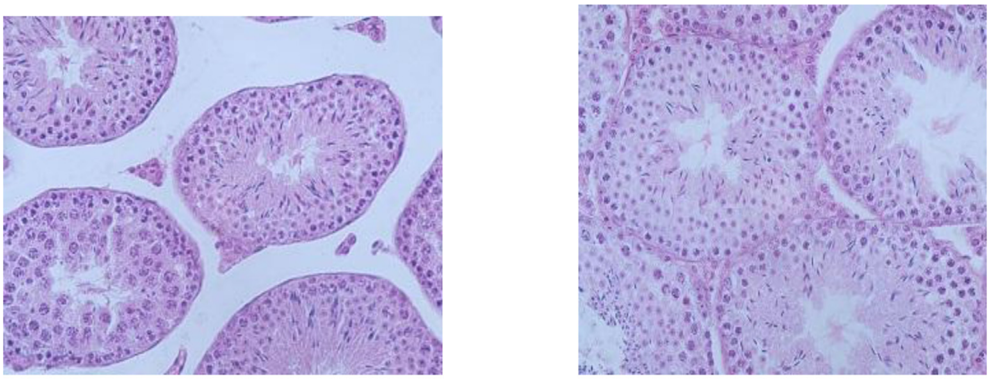
4. Empirical outcomes

The empirical outcomes of a proposed methodology would be explained and presented in this section. C# language is utilized to implement the suggested method. Two types of datasets such as high plasma' temperature of mice and plasma of microwave would be utilized for suggested method estimation. The number of images used for microwave plasma are 25 and high plasma' temperature are 18 images. Images in dataset are colored JPEG with size 320 × 240 pixels. The proposed methodology involves multiple stages: -



a) points of data which are distributed **b) First acquired representation**

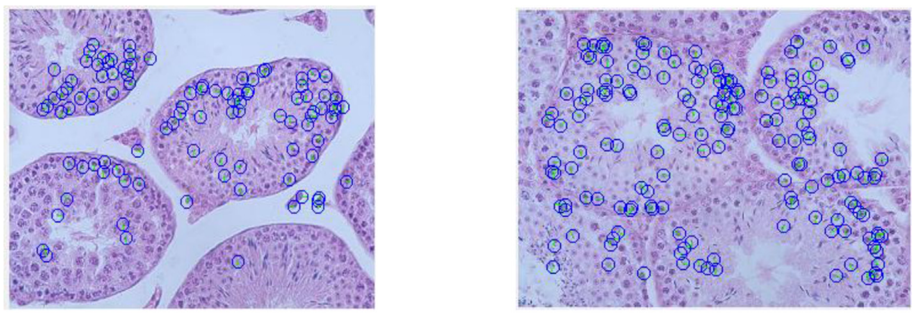
Fig. 6. Sample of points of data [17].



a) **b)**

Fig. 7. Plasma images a) high temperature of plasma b) plasma of microwave.

1) A process of loading the images of plasma onto the project's form can be carried out in the head-most stage as explained in Fig. 7-a, for high plasma's temperature and 7-b for plasma of microwave.
2) Secondly, employing AGAST detector for detecting the corners. The descriptors are computed via FREAK descriptor. Fig. 8 explains a detector stage and a descriptor stage, (a) with high plasma's temperature and (b) with plasma of microwave.



a) **b)**

Fig. 8. The descriptor of FREAK with a detector of AGAST, a) high plasma's temperature b) plasma of microwave.

Hot Plasma

Image Name	STD
Plasma_1	36
Plasma_13	36
Plasma_15	37

a)

Cold Plasma

Image Name	STD
Plasma_10	28
Plasma_11	17
Plasma_12	17
Plasma_14	22
Plasma_2	28
Plasma_3	28
Plasma_4	22
Plasma_5	20
Plasma_6	28
Plasma_7	28
Plasma_8	20
Plasma_9	18

b)

Fig. 9. Images classification, a) Plasma of Hot, b) Plasma of Cold.

3) Standard deviations were calculated at the third stage of the suggested method and then whole images in dataset can be classified relying on their standard deviations by employing KNN. From the calculations conducted on several images show that the value of standard deviation of sperm images when affected by hot plasma exceeds 30. Therefore; they use the value > 30 to positive classification. Fig. (9) explains a stage of classification to whole images within its STD. High or hot plasma's temperature illustrated in (a) and plasma of microwave or cold illustrated in (b).

5. Conclusions

It is the aim of this research to classify the type of plasma that affecting sperm in mice. A methodology utilized the detector of AGAST to elicit interesting characteristics out of the images of plasma which is better and faster than the detector of FAST. An AGAST alters the FAST's low-level decision trees. ID3 was utilized for constructing FAST's decision tree, that is a grasping approach and the outcome is completely suboptimal, whilst AGAST employs the binary tree instead of the ID3 that makes it more effective than FAST. When merging two trees, there is no need for AGAST to be trained whereas keeping the same response of corner repeatability and response like FAST reproducer. The FREAK was a binary descriptor that can be computed relying on brightness' outcomes of contrasting practices in a sampling position number over a key point. FREAK method does not include a stage for detectors of key points, it only relies on presenting the detectors' key points, and usually the corner detector of AGAST. The descriptor of FREAK is much elaborate and powerful. KNN (K-Nearest Neighbors) was calculated in the third stage for images classification depending on the STD amount. From the calculations conducted on several images show that the value of standard deviation (STD) of sperm images when affected by hot plasma exceeds 30. The outcomes of the experimental work illustrated that; plasma_3 has a STD value of 28 therefore; this image is classified under an image affected by cold plasma, while plasma_1 has the STD value is 36 and plasma_15 has the STD value is 37 therefore; these image are classified under images affected by hot plasma. KNN is solid for noisy data training and it is effective for very large data training as well.

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