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A Survey analysis for the detection of canine diseases among domestic mammals using image texture pattern extraction methods

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***Abstract*— In an information-intensive culture, computer technology has begun to reach other conventionally realizable sectors. Alongside this trend, several high-tech machines have emerged. Concurrently, a variety of high-tech devices have emerged in the traditional medical area in order to aid physicians in the treatment process. The introduction of sophisticated picture recognition technology has decreased a significant amount of the doctor's effort required to evaluate the tiny sick cells within the human body. The modernization, rationalization, and intelligence of the design and production of illness detection equipment utilizing image extraction technologies are increasing. In the medical industry, feature-based image recognition technology disease diagnosis equipment analyses and diagnoses pathology using picture collecting. From 2018 to 2022, the current study examines several image extraction algorithms applied to the identification of canine illnesses. Using classification, researchers have reached a high level of sensitivity and specificity in medical picture analysis. This evaluation not only identifies obstacles, but also identifies and presents fresh research prospects for this field's scholars.**

Keywords—Cancer, Data features, Machine learning, Oncology, Prediction system, Survey

I. INTRODUCTION

Most health specialists are persuaded of the intimate relationship between human and veterinary care, and that the advantages derived from such a connection can be rather apparent when analyzed in the proper context [1]. Several international organizations have emphasized the importance of this notion. To name a few, the World Health Organization (WHO), the World Organization for Animal Health (Office International des Epizooties, OIE), the Food and Agriculture Organization of the United Nations (FAO), the American Medical Association (AMA), and the American Veterinary Medical Association (AVMA) [2] have highlighted its significance.

Numerous sources may assist in establishing the veracity of the referenced relationship. The most objective data likely derives from a single aspect of the disease: its transmission from animals to people, or classical zoonosis [3], and from humans to animals, or zooanthroponosis [4]. Other equally fascinating, important, and illustrative ways include animal testing, animal transplantation, and animal research [5], which have led, among other accomplishments, to xenotransplantation [2], [6]. Particularly significant are instances in which pigs are employed as donors. Understanding the genomes of humans and other species has aided in bringing human and veterinary care closer together and strengthening their bond [7]. Unfortunately, several medical specialties that may bring useful new techniques are not being considered. One of these is the presentation of malformations, dysmorphias, or abnormalities, which is a well-researched topic in human medicine but less so in veterinary medicine, and much less so from a comparative standpoint.

Canine Diseases

Babesia piroplasmid organisms parasitize numerous animals. B. caballi is one of two piroplasmid organisms responsible for babesiosis (or piroplasmosis) in domestic equids, a condition characterized as "the most severe infectious illness of horses in southern Africa." Widespread ticks serve as vectors for these two parasites, and T. equi appears to have originated as an infection of zebras [8]. Heartwater and monocytic ehrlichiosis in dogs Both of these disorders are caused by Ehrlichia rickettsias. Ehrlichia canis, the pathogen responsible for the first, is transmitted only by Rhipicephalus sanguineus, the brown dog tick.

Traditional substances include drugs, explosives, human fragrance, and human remains, whereas less prevalent or developing substances include illnesses, pests, and animals. This variety of objectives is reflected in the professional community. The training techniques and procedures of canine teams are influenced by the opinions, research, and experience of canine handlers and trainers, behavioral sciences, genetics, veterinary medicine, and analytical sciences, as well as other organizations and government agencies. This abundance of

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knowledge has made the dog community innovative and prosperous. Nonetheless, there is a significant lack of consensus within the community over a standard nomenclature. This discrepancy hampers the transmission of information across the canine sector, hindering technological and methodological progress. [8], [9]

Image texture pattern extraction system

Textural characteristics are crucial for determining the content of a medical picture. Textural characteristics contribute to scenic depth, the spatial distribution of tonal variation, and the orientation of the surface. A CBIR system was constructed using several feature extraction techniques, including discrete wavelet frame, HU moment invariant, Fourier transform, gray-level histogram (GLH), and gray-level coherence vector. The grey level co-occurrence matrix and the grey level run length matrix are two well-known techniques [10, 11]. We studied these strategies for extracting characteristics from medical pictures since they have some success in textural image categorization. [12].

Objectives of this paper are as follows:

- To study the basic introduction in-detail about disease detection in domestic mammals.
- To study the methodologies related to image texture pattern extraction method used in diseases detection.
- To study and analyse the existing technical algorithms about their working process.
- To study and analyse the results and comparison with table and graph referred from existing studies.

The paper is divided into five sections. Section I consists of an introduction to the subject of the survey and a basic explanation of key ideas. Methodologies associated with picture texture pattern extraction for illness detection are discussed in Section II. The description and study of the functioning process of existing technological algorithms is the focus of section III. The part IV focuses on the research and analysis of the data, as well as their comparison with tables and graphs from previous studies. Final section V offers the paper's conclusion and future proposals for the suggested work.

II. Background Study

The purpose of "Texture Shape Extraction" is to extract 3D pictures covered by a certain texture from an image. This discipline investigates the structure and form of the image's parts by studying their textual qualities and spatial relationships. Texture Synthesis is designed to generate pictures with the same texture as the input texture. This field has applications in the generation of visual pictures and computer games. Other uses of this field include the elimination of a portion of a picture and its replacement with the backdrop texture which used Ant colony features [13], the construction of a scene with lighting and a variable viewing angle is like similar done by ants, and the development of aesthetic effects on photos, such as embossed textures.

The objective of "Texture Segmentation" is to separate a picture into discrete sections with distinct texture characteristics. Texture segmentation identifies the boundaries between several textures. In other words, in texture segmentation, the properties of the borders and regions are compared, and the boundary range is determined if their texture characteristics are sufficiently distinct. Texture classification is one of the key topics within the framework of texture analysis, whose primary function is to offer descriptors for classifying textural pictures. [12], [13] Texture classification involves allocating an unidentified picture from K-means clustering sample to one of the established texture classes. As stated earlier, texture classification involves assigning an image sample to a previously specified texture category. This categorization often requires two steps.

A. The initial step, the phase of feature extraction:

The initial step in extracting texture characteristics is to develop a model for each texture included in the images. At this level, the extractive features may be numerical, discrete histograms, empirical distributions, textural features such as contrast, spatial organisation, and direction, etc. These characteristics are used to instruct categorization. Numerous approaches for categorising texture have been presented thus far, the effectiveness of which is highly dependent on the characteristics recovered. They may be split into four primary categories, including "statistical techniques," "structural methods," "model-based approaches," and "transform methods." Each of these techniques extracts distinct textural characteristics [14]. It is important to note that, due to the complexity of the approaches and the usage of integrated attributes, it is currently challenging to categorise the majority of them into a single group.

B. The second stage, the classification phase:

In this phase, the texture of the test sample picture is examined using the same method as in the preceding stage. Then, using a classification algorithm, the extracted characteristics of the test image are compared with those of the train imagery, and the class of the test image is decided. Based on the two prior steps, Fig. 1 depicts the overall flowchart of approaches for texture image categorization. At the conclusion, the estimated classes for testing are adapted to their actual class, and the recognition rate, which indicates the efficacy of the implemented method, is calculated. The recognition rate of each algorithm is used to compare the efficacy of its algorithm with other available methods. [15]

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$$Classification\ accuracy = (Number\ of\ correct\ Matches\ /\ Total\ Number\ of\ test\ images) \times 100\%$$

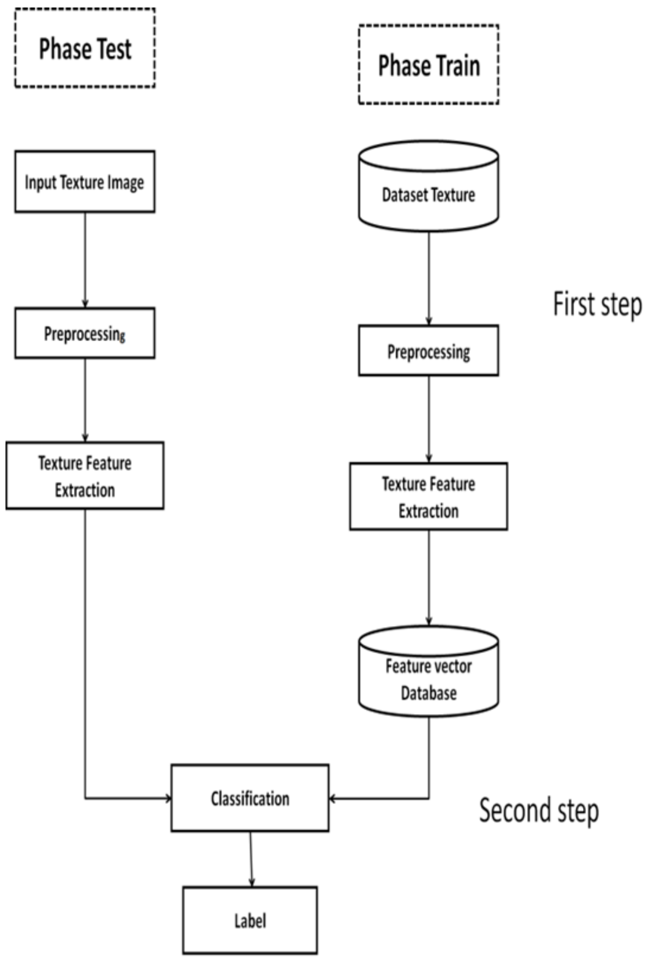

Fig. 1: The popular flowchart of the texture images classification process [15], [16]

C. Texture Analysis Application:

The picture texture provides a wealth of information on the image's subject matter, objects, background context, backdrop, etc. Texture analysis is utilized in most image processing fields, particularly in the learning and feature extraction processes. [17]

III. Survey of Existing Techniques

Domestic Mammals (DM) shall mean, for the purposes of this article, a group of animals that includes cows, sheep, goats, pigs, horses, dogs, and cats. This section focuses solely on DM because they are the most thoroughly researched species in the veterinary sector. Using a specific group of animals, in this example the DM, it is believed that the one health idea will be easier to implement and more objectively attainable. [2], [5] The abnormalities that have historically attracted the attention of experts are those with macroscopic and exterior symptoms, and more specifically, those with significant deformities or monstrosities. Ruminants and swine belong to the category of animals known as production animals or animals for slaughter, horses are mostly employed for sport and recreation, while dogs and cats are considered pets or companion animals. As stated previously, developmental abnormalities (DA) in veterinary science have not been the topic of thorough research in the field of DM, despite the existence of a sufficient number of well-documented examples [18]. Four examples found with relative frequency in cows have been selected: hydrocephalus (Fig. 2) [18], bicephalous (Fig. 3) [6], cleft palate or palatoschisis (Fig. 4), and congenital flexed pastern (Fig. 4), the latter described in humans as congenital wrist flexion contracture, a type of arthrogryposis. [8]

Fig. 2: Lateral view of two different cases of hydrocephalus in cattle, showing marked enlargement of the head [8]

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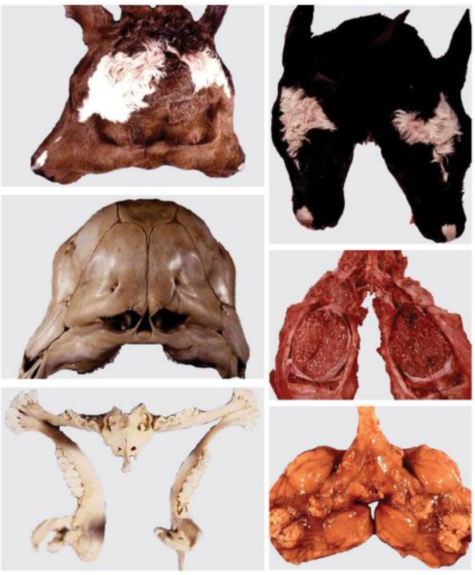

Fig. 3: Two different cases of bicephalous or two-headed in cattle [8]

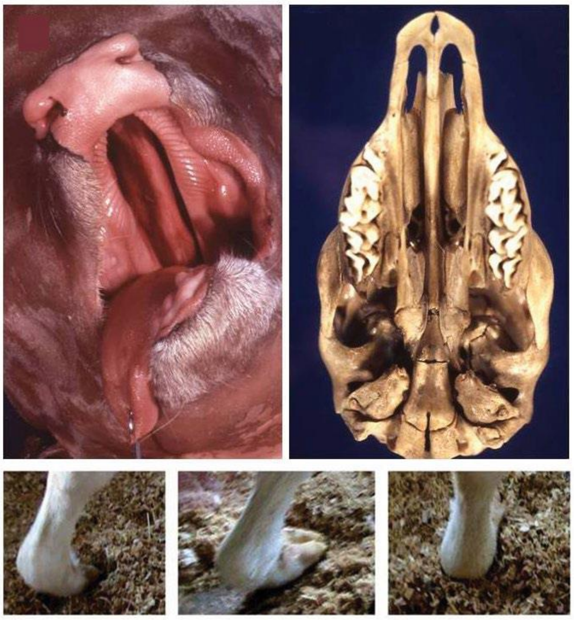

Fig. 4: Top, ventral view of the roof of the oral cavity showing a typical case of cleft palate or palatoschisis in cattle [8]

Concurrently, the study of the dog genome has yielded a wealth of information pertinent to the manifestation of certain DA due to breeding genetic predisposition or tendency (Canine Inherited Disorders Database [19], Guide to Congenital and Heritable Disorders in Dogs [20], Inherited Diseases in Dogs, List of Inherited Disorders in Animals, Online Mendelian Inheritance in Animals database). This issue's significance has led to the expansion of specific multinational programs, such as the LUPA project [20], whose data have been frequently updated since its commencement. It is essential to remember that the estimated number of dog breeds exceeds 400, of which about half are officially recognized. Individual dog lineages have suffered molecular genetic alterations and mutations as a result of the intense artificial selection that occurred during domestication as a result of the vast variety of breeds [21].

A. *Gray level co-occurrence matrix*

Gray-level co-occurrence matrix (GLCM), originally suggested by M. Haralick, is a measure of the gray-level dependency of texture in spatial domain. After acquiring the GLCM matrix of the picture to be assessed, statistical computations are conducted on this matrix to generate a comparative feature vector. Although numerous statistical functions have been proposed for use as a feature in a feature vector, energy, entropy, homogeneity, contrast, and correlation are the most frequently recognised statistical approaches [11], [22]. Therefore, we incorporated these five textural properties into the feature vector.

B. *Gray level run length matrix*

The run of a texture is as near as possible to the sequence of gray-level pixels in a line. Then, these may be recognised as grey level, length, and direction expressions. [23] Texture-defining characteristics can be calculated based on the probability of length and grey level of run-in texture. The Gray Level Run Length Method (GLRLM) is based on calculating the number of grey levels with varying lengths. The length of a grey level is the linear series of adjacent picture points with the same grey level value. The number of picture dots makes up the length of a grey level [24, 25]. Galloway proposed using a run length matrix to extract texture features.

C. *Gabor wavelet filtering*

The characteristic of the Gabor wavelet transformation is to share similarities with the human visual system, particularly in terms of frequency and orientation representation. It isolates several filtered pictures with minimal frequency variations and intensity trends. These characteristics are also deemed suitable for distinguishing the texture [26, 27].

Table 1: Existing studies based on diseases detection using image extraction techniques

Author name	Year	Name of paper	Technology used
K.Balasamy and D. Shamia [11]	2021	Feature extraction-based medical image watermarking using fuzzy-based median filter	GLCM
Y. Zhang et. al. [22]	2016	Theano: A Python framework for fast computation of	GLCM

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		mathematical expressions	
J. O. Shea [23]	2017	Digital disease detection: a systematic review of event-based Internet bio surveillance systems	GLRIM
R. Zhang and B. Xin. [24]	2016	A review of woven fabric pattern recognition based on image processing technology	GLRIM
L. Wei et. al [25]	2016	A rapid automatic analyzer and its methodology for effective bentonite content based on image recognition technology	GLRIM
T. Tatsuya et. al. [26]	2016	Use of image recognition technology in information device	Gabor wavelet image filter
L. Farotti et. al. [27]	2016	Performance evaluation of an automated ELISA system for alzheimer's disease detection in clinical routine	Gabor wavelet image filter

IV. Detection of Canine using Image extraction

The use of biomedical detection dogs for various infectious and non-infectious diseases such as Helicobacter pylori, various types of cancer [2]– [5], hypoglycemia in diabetes patients [23]-[27], epileptic seizures [28], bacteriuria, bovine virus diarrhea, COVID-19 [4], [28], Malaria, and Clostridium difficile-infections is still in its infancy (Table 2). Most of these investigations reveal a disease-specific body odour or a distinct volatile organic compound (VOC)-pattern linked with metabolic alterations caused by an illness [36]. This also uses genetic algorithm for infection analysis [29]. In the event of a viral infection, VOCs are produced only by the host cell, but for bacteria, VOCs are produced by both the host and bacterium.

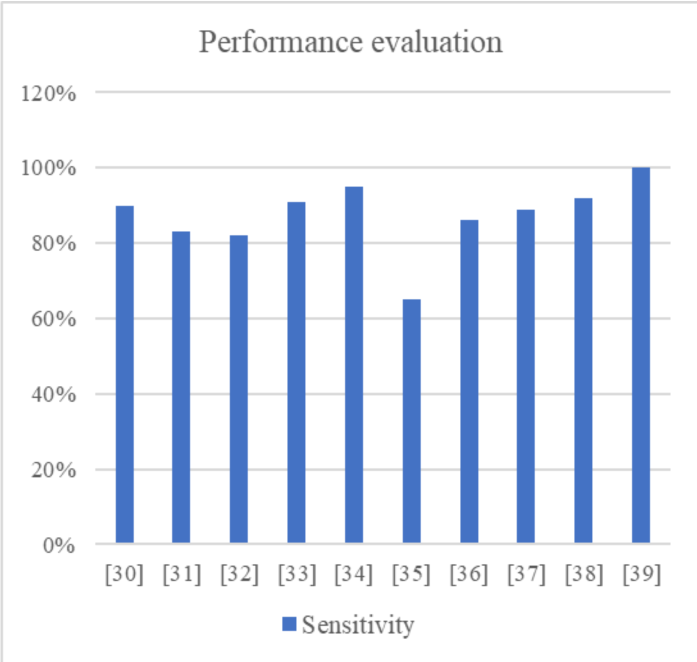

Fig. 5: Performance comparisons of existing techniques based on sensitivity

Infectious disorders are more amenable to canine medical detection than non-infectious diseases like cancer, diabetes, and epileptic convulsions. Despite some apparently promising research on medical canine smell detection, published findings for the diagnosis of cancer might differ greatly. Different forms of cancer, such as bladder, prostate, or ovarian cancer, lung and breast cancer, as well as colorectal neoplasms, have been identified by trained sniffer dogs with wildly divergent outcomes in scientific studies. Compared to histology, diagnostic accuracy varied, with sensitivities ranging from 82 to 100 percent (figure 5) and specificities from 88 to 99 percent (figure 6) [30]– [39]. Different sample materials, such as urine, blood, breath, or faces, were utilized

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for presentation, which might explain the variation in findings. Lack of uniformity of training and trainer bias, which may have a significant effect on the training outcomes of detection dogs, are additional factors that contribute to the heterogeneity of the findings.

Fig. 6: Performance comparisons of existing techniques based on specificity

Table 2: Detection of canine disease using image extraction

Publication	Authors	Detection of	Results
Trained dogs identify people with malaria parasites by their odor	Guest et al. (2019) [30]	Malaria infection	Sensitivity 72% Specificity 91%
Using Dog Scent Detection as a Point-of-Care Tool to Identify Toxigenic Clostridium difficile in Stool	Taylor et al. (2018) [31]	Toxigenic *Clostridium difficile*	Sensitivity 85% Specificity 85%
A Proof of concept: Are Detection Dogs a Useful Tool to Verify Potential Biomarkers Biomarkers for lung cancer?	Fischer-Tenhagen et al. (2018) [32]	Lung cancer	correct identification average 95%, correct negative indications average 60%
Accuracy of Canine Scent Detection of Non–Small Cell Lung Cancer in Blood Serum	Junqueira et al. (2019) [33]	Non–small cell lung cancer	Sensitivity 97%, Specificity 98%
How dogs learn to detect colon cancer-Optimizing the use of training aids	Schoon et al. (2020) [34]	Colon cancer	Average hit rate 84% Average false positive rate 12% (for new unknown samples)
How effective are trained dogs at alerting their owners to changes in blood glycaemia levels? Variations in performance of glycaemia alert dogs	Rooney et al. (2019) [35]	Hypoglycaemia	Median sensitivity 83%
Variability of Diabetes Alert Dog Accuracy in a Real-World Setting	Gonder-Frederick et al. (2017) [36]	Hypoglycaemia	Sensitivity 57% Specificity 49%
Reliability of Trained Dogs to Alert to Hypoglycemia in Patients with Type 1 Diabetes	Los et al. (2017) [37]	Hypoglycaemia	Sensitivity 36%
Dogs demonstrate the existence of an epileptic seizure odour in humans	Catala et al. (2019) [38]	Epileptic seizure	Sensitivity 87% Specificity 98%
Canine detection of volatile organic	Maa et al. (2021)	Epileptic seizure	Probability of distinguish

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compounds unique to human epileptic seizure	[39]		ing ictal versus interictal sweat 93% Probability of canine detection of seizure scent preceded clinical seizure 82%

V. Conclusion

Texture may be described in image processing as a function of the spatial variation of pixel brightness intensity. Texture is the primary phrase used to describe the objects or concepts within an image. Texture analysis is crucial for computer vision applications such as object recognition, surface defect detection, pattern recognition, medical picture analysis, etc. Since then, several methods have been presented to adequately characterize texture pictures. Methods for texture analysis are often divided into four categories: statistical, structural, model-based, and transform-based. This study explains in depth the various techniques used for texture or analysis. Although various research have been provided, generic medical picture archiving systems are not particularly effective.

In this work, the retrieval performance of spatial approaches utilized for feature extraction in medical image retrieval systems is investigated. As acknowledged spatial approaches, grey level co-occurrence matrix (GLCM), grey level run length matrix (GLRLM), and Gabor wavelet are utilized to analyze existing research. In the trials, a database including hundreds of medical photos, including brain, lung, sinus, and bone, is compiled. This study's findings indicate that inquiries based on statistics derived from GLCM are fulfilled. Compared to histology, diagnostic accuracy ranged from 82 to 100 percent sensitivity and 88 to 99 percent specificity [30]–[39]. The future of machine learning techniques in medicine and other sectors is quite promising.

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