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Bouzid Mohammed Walid

Biomedical engineer student

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TIRADS Based Thyroid Nodule Classification Using Texture Exploiting Descriptors

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PRESIDENT	**MR. BECHAR MOHAMMED AMINE**	***MCB***	**TLEMCEN UNIVERSITY**
ENCADREUR	**MR. GAOUAR ADIL**	***MCB***	**TLEMCEN UNIVERSITY**
EXAMINATRICE	**MME. KAZI**	***MCB***	**TLEMCEN UNIVERSITY**

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Preface

This report on "TIRADS Based Thyroid Nodule Classification Using Texture Exploiting Descriptors" is prepared under the guidance of Mr. GAOUAR ADIL

Through this thesis we have tried to give a detailed design of a classification system for thyroid nodules and try to cover every aspect of the system.
We have tried to the best of our abilities and knowledge to explain the content in a lucid manner. We have also added graphs, tables and figures to make it more illustrative.

Abstract

Researchers have developed Computer-Aided Diagnosis (CAD) systems to help doctors diagnose thyroid nodules to reduce traditional methods errors. Doctors' experiences are the basis of the traditional diagnosis methods. Therefore, such systems' performance plays a vital role in enhancing the quality of a diagnosing task. Although state-of-the-art studies regarding this problem are based on handcrafted features, deep features, or the two's combination, their performances are still limited. To overcome these problems, we propose an ultrasound image-based diagnosis of the malignant thyroid nodule method using artificial intelligence. We have used a two-stage classification to classify the thyroid nodules into its respective TIRADS score in this work. Our experiments with a popular open dataset, namely the Thyroid Digital Image Database (TDID), confirm our method's superiority compared to state-of-the-art methods.

Key words: Computer-Aided Diagnosis systems (CADs), Thyroid, TIRADs, Thyroid Digital Image Database (TDID), SVM, artificial intelligence (AI).

RÉSUMÉ

Des chercheurs ont mis au point des systèmes aid à décesion médical (SADM) pour aider les médecins à diagnostiquer les nodules thyroïdiens afin de réduire les erreurs liées aux méthodes traditionnelles. L'expérience des médecins est à la base des méthodes de diagnostic traditionnelles. Par conséquent, les performances de ces systèmes jouent un rôle essentiel dans l'amélioration de la qualité d'une tâche de diagnostic. Bien que les études de pointe concernant ce problème soient basées sur des caractéristiques artisanales, des caractéristiques profondes ou une combinaison des deux, leurs performances sont encore limitées. Pour surmonter ces problèmes, nous proposons une méthode de diagnostic du nodule thyroïdien malin basée sur les images échographiques et utilisant l'intelligence artificielle. Dans ce travail, nous avons utilisé une classification en deux étapes pour classer les nodules thyroïdiens en fonction de leur score TIRADS respectif. Nos expériences avec un jeu de données ouvert populaire, à savoir la base de données d'images numériques de la thyroïde (TDID), confirment la supériorité de notre méthode par rapport aux méthodes de pointe.

Mots clés : systèmes aid à décesion médical (SADM), Thyroïde, TIRAD, Base de données d'images numériques de la thyroïde (TDID), SVM, intelligence artificielle (IA).

ملخص

لمساعدة الأطباء في تشخيص عقيدات الغدة الدرقية لتقليل أخطاء (CAD) طور الباحثون أنظمة التشخيص بمساعدة الكمبيوتر الطرق التقليدية. خبرات الأطباء هي أساس طرق التشخيص التقليدية. لذلك ، يلعب أداء هذه الأنظمة دورًا حيويًا في تحسين جودة مهمة التشخيص. على الرغم من أن الدراسات الحديثة المتعلقة بهذه المشكلة تستند إلى ميزات مصنوعة يدويًا أو ميزات عميقة أو مزيج من الاثنين ، إلا أن أدائهم لا يزال محدودًا. للتغلب على هذه المشاكل ، نقترح التشخيص القائم على الصورة بالموجات فوق الصوتية لطريقة العقيدات الدرقية الخبيثة باستخدام الذكاء الاصطناعي. لقد استخدمنا تصنيفًا من مرحلتين لتصنيف العقيدات الخاصة بها في هذا العمل. تؤكد تجاربنا مع مجموعة البيانات المفتوحة الشائعة ، وهي قاعدة بيانات TIRADS الدرقية في درجة ،، تفوق طريقتنا مقارنة بأحدث الأساليب (TDID) الصور الرقمية للغدة الدرقية.

الكلمات الرئيسية: أنظمة التشخيص بمساعدة الكمبيوتر (CADs) ، الغدة الدرقية ، TIRADs، قاعدة بيانات الصور الرقمية للغدة الدرقية (TDID) ، SVM، الذكاء الاصطناعي.(AI)

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We thank, above all, Allah, the Almighty, for granting me among his countless grace, health and will to accomplish this work.

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I would also like to thank the professors and teachers of the biomedical engineering department as well as its students and staff who worked with us throughout our university course.

That anyone who has worked directly or indirectly for the realization of this project by any form of contribution, find here the testimony of my deepest gratitude

Dedication

I Dedicate My Dissertation Work to My Family and Many Friends. A Special Feeling of Gratitude to My Loving Parents to My Mother with All My Passion, To My Father with All My Gratitude Whose Words of Encouragement and Push for Tenacity Ring in My Ears.

My Sisters Who Never Left My Side and Are Very Special.

To My Dear Brother.

To My Family.

I Also Dedicate This Dissertation to My Many Friends and Family Who Have Supported Me Throughout the Process. I Will Always Appreciate All They Have Done, Especially Briki Amine for Helping Me Develop My Technology Skills, Barrouchi Oussama For the Many Hours of Proofreading.

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INTRODUCTION

A thyroid nodule (or lump) that creates in a human's thyroid organ is an illness wherein cells develop strangely and are probably going to spread to different pieces of the body (Cancer.Net, 2020). The presence of this nodule might possibly be a sign of thyroid disease. At the point when a thyroid nodule is found, an ultrasound of the thyroid district is done to affirm whether that nodule is, indeed, a cancerous/non-cancerous nodule, which in clinical terms is alluded to as a benign/malignant nodule, individually. Luckily, the vast majority of the thyroid nodules recognized are benign. Notwithstanding, the presence of the nodule (regardless of whether benign or malignant) causes different medical conditions in patients, like trouble in breathing and swallowing (Nguyen et al., 2020). Furthermore, threatening thyroid nodules can create an extra hormone called thyroxine, which prompts basic medical conditions and can prompt the death of the patient. In this way, characterizing these nodules at a beginning phase can reduce the danger of patient death.

Anomalies like throat dryness, swelling of the organs in the neck, trouble swallowing, trouble breathing, pain in the throat or neck, a lump toward the front of the neck (close to the apple of Adam), and so on are side effects of thyroid disease (Cancer.Net, 2020). There are a few imaging methods for analyzing the thyroid, like computed tomography (CT), ultrasound (US), x-ray, and so on (Cancer.Net, 2020). Ultrasound imaging is the most effective tool for the early recognition of thyroid malignant cancer. It utilizes high-frequency sound waves to make a picture of internal organs (Cancer.Net, 2020; Nguyen et al., 2020).

CAD systems for thyroid nodule classification comprise of fundamental modules: preprocessing thyroid ultrasound images, image enhancement, highlight extraction, and classification. The preprocessing step assists eliminate backgrounding and artefacts (extra content or indicator made by the capturing system). Enhancement procedures are applied to the thyroid images to work on the representation of tissues or a tumor. At last, a feature extraction procedure is utilized to acquire the features from pictures and a classifier to classify them.

Thyroid images can be better classified by using their texture properties (Chang et al., 2010). We use the following two descriptors that capture the textural features for classifying thyroid nodules, i.e., the Histogram of Oriented Texture (HOT) and Pass Band - Discrete Cosine Transform (PB-DCT). We use Discrimination Potentiality (DP) to select the appropriate features. These proposed descriptors are compared with the existing standard methods for thyroid nodule classification; image augmentation (Zhu et al., 2018), VGG-16 (Simonyan & Zisserman, 2015), Google Net(Sai Sundar et al., 2019), Circular Mask(Nguyen et al., 2019), and Convolutional Neural Network (CNN). (Nguyen et al., 2019) Support Vector Machine (SVM) is the most suitable and widely used classifier for the two-class classification problem. Hence, we use SVM as a classifier.

Problem statement

The customary diagnostic technique, where specialists analyze cancerous tumors from pictures (CT, US, X-rays, and so on), can in some cases give mistaken outcomes since this finding depends heavily on the individual information and experience of the patient, specialist. Also, it is hard for specialists to decide if a thyroid nodule is benign or malignant dependent on indications or experience. This is the reason, these days, scientists are focusing on the improvement of imaging methods dependent on artificial intelligence (AI) (Nguyen et al., 2019, 2020). The advancement of image-based computer-assisted diagnostic (CAD) systems in clinical research fill in as extra aptitude to help doctors make precise diagnoses.

That’s why we have proposed a two-stage classification methods system that’s based on enhancement of the texture properties of the ultrasound image in this work, based on TIRADS scores.

First we se the preprocessing and enhancement technique that contains (image binarization, image normalization and image enhancement), the main goal of this step is to remove background artifact that comes with the original image from the capturing system configuration then we apply the output of this methods as an input for our features extraction technique we proposed Histogram of Oriented Texture (HOT) and Pass Band - Discrete Cosine Transform (PB-DCT)

And before the last stage we apply a customize feature selection technique Discrimination Potentiality (DP) to select the most suitable features for to our classification system.

In the first stage, the thyroid nodules are classified as benign and malignant. In the second stage, benign nodules are further classified as nodules with TIRADS scores 2 and 3, and malignant nodules are classified as nodules with TIRADS scores of 4 and 5.

The work carried out within this framework and the results obtained are gathered in a Master's thesis organized in the following way:

In the first chapter the decision is the starting point for the study of medical decision support systems. It defines the functionalities and the steps to be implemented in order to achieve the objectives of the medical decision process. As such, the first chapter constitutes a general presentation of the decision and medical decision support. First, we present the basic concepts, the decision-making process and decision support. We then discuss Computer-Aided Diadnosis Systems (CADs).

The second chapter will present some of the related works to our study and also the related works of the TI-RADS scoring systems that been presented by famous and major universities and even countries.

The third chapter will discuss the preposed methods to our study, it begin with the pre-processing and enhancement techniques from image binarization normalization and enhancement, then we present our feature extraction technique (HOT) with (PB-DCT), then lastly we discuss the feature selection and minority oversampling briefly

Then last but not least in the forth chapter will be presenting experimental results beginning with presenting our dataset (TDID) and our result with the comparison to other works.

Chapter 1

Computer-Aided Diagnosis Systems (Cads)

1.1 Introduction

While the goal of decision sciences is to track down an ideal decision dependent on an evident target vision of the real world, decision help is keen on the development of agreeable decisions by considering every one of the emotional measurements that can show up during a decision-making measure. Above all else, a qualification should be settled on between the specialist and the decision-maker, for example between the master in decision support techniques and the individual or gathering of individuals responsible for making decisions. The reason for decision support is to make these two principal entertainers act together to settle on decisions arise. Decision-making for the most part includes extraordinary, even conflicting, perspectives. The assignment of the decision-maker is then to demonstrate the inclinations of the decision-maker by drawing out the various perspectives, or measures on which the decision is situated according to the decision-making circumstance or issue and which will be considered in the decision-making measure. The blend of AI and decision support systems gives another IT help to decision-makers by broadening their thinking capacities in complex

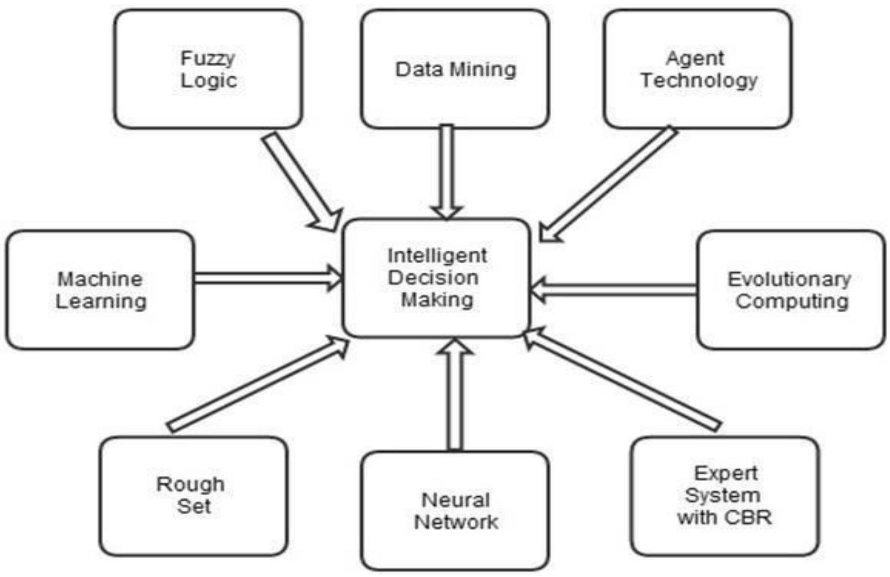


Figure 1. intelligent techniques in decision support (Das, 16).

conditions. Decision support systems with "insight" and space ability have been concentrated widely by numerous analysts. Intelligent procedures are valuable for breaking down information and giving expectations, evaluating vulnerability, effectively giving data, and recommending the path forward. features how decision making is affected by a different scope of intelligent strategies Figure 1.

1.2 Decision and decision support

Decision-making and its execution are the objectives of any decision-making issue in an association. For the duration of the existence of an association, decisions are consistently settled on inside it by decision-makers. Decisions are frequently made based on realities identified with an issue and encounters. In certain pretty much fragile circumstances, the decision-maker is helped via programmed techniques to direct him in his selection of arrangements and this decision task turns out to be significantly more exhausting and exorbitant, it along these lines gets important to utilize Interactive decision support systems, noted: IDSS.

For the realist scientific schools, the decision is characterized as a decision between a few options(Schneider, 1996). For other people, the decision additionally concerns the way toward choosing choices. Intellectual methodologies treat the decision as the aftereffect of a worldwide critical thinking measure(Schneider, 1996). This implies that the term decision has a few definitions. It is utilized to assign a demonstration, an activity or a critical thinking measure. Different creators propose different definitions, each mirroring an alternate perspective.

Definition 1:

Roy and Bouyssou look at that as a decision is frequently introduced as: "the demonstration of a detached individual (decision-maker) who uninhibitedly practices a decision between a few potential activities at a given second on schedule" (Bernard Roy & Bouyssou, 1993).

Definition 2:

Levine and Pomerol characterize the decision as follows: "A decision is a move that is made to manage a trouble or react to an adjustment of the climate, that is, to take care of a difficult that emerges for the individual or the association" (Pomerol, 1990).

Definition 3:

As per Mintzberg et al, "a decision, regardless of whether individual or coming about because of a collective endeavor, can be characterized as a promise to activity, i.e., an unequivocal expectation to act"(Mintzberg et al., 1976).

- Qualities of the decision.

The decision is described by:

- *Its motivation.*

It permits us to recognize key, strategic and operational decisions. The essential decision concerns the organization's relations with the climate and basically concerns the selection of business sectors and items to adjust the organization to its current circumstance. The strategic decision is identified with the administration of assets which are obtaining, association and improvement. The operational decision is identified with the current activity. Its motivation is to make the asset change measure more proficient (Mansoul, 2020).

- *Its deadline.*

This makes it conceivable to recognize:

- momentary decisions that just have an impact throughout a brief timeframe
- medium-term decisions that submit the organization more than quite a long while
- long haul decisions that are remarkable (Mansoul, 2020).

- *Its level of construction*

The number and intricacy of the boundaries associated with a decision cycle can shift incredibly. At the point when the boundaries are not many, effectively recognizable and quantifiable, it is feasible to "formalize" the decision, for example, to utilize a standard goal system or to foster a decision-making model. Any issue is then exposed to a progression of tasks completed in an exact request and under specific requirements, to go from the fundamental data to the last decisions (Mansoul, 2020).

Besides, man is frequently stood up to with circumstances where he is confronted with various theories to decide the best circumstance for him. The present circumstance of decision between a few arrangements is frequently founded on the advancement of one or a few target measures. These circumstances of decision are treated in the decision hypothesis. To be sure, the decision hypothesis unequivocally accepts the accompanying assertions :

- the presence of the best decision that can be reached with time and assets;
- this best decision can be ideal, in the event that we figure out how to enhance a model;
- this ideal decision is consistently reachable through a cycle.

According to Roy, decision support is: "*an activity based on rigorous concepts, methodologies, models and techniques. It aims to clarify the decisions to be made by a stakeholder, without dictating his conduct*"(B. Roy, 1986). It goes with the decision-making measure by carrying illumination to it without subbing itself for the decision-making which is the sole obligation of the decision-maker. Schärlig sees that this definition is short-sighted, however it expresses the need to depend on models, and not to make them say the arrangement, it implies components of reaction as opposed to finish and conclusive answers, it alludes to the partner instead of to the decision-maker, it specifies the need to illuminate the decision as opposed to figure out which is the best arrangement (Schärlig, 1985).

From this, we can say that decision support depends on models to help an entertainer in the decision-making cycle to acquire answers to the inquiries he poses to himself. This decision help can prompt a remedy that permits to orientate towards an answer (decision). It's anything but a cycle that utilizes a bunch of accessible data to define an issue and arrive at a decision on a particular article. Nonetheless, Roy sees that the order of decision support did not depend on the presence of unadulterated fact of the matter. What's more, if this fact should exist, the target will be to direct and illuminate the decision-maker all through the decision-making measure(Bernard Roy, 1993) . Accordingly, we will at this point don't attempt to track down "the best decision" however to go with the decision-maker by attempting to draw out the target perspectives and those which are less thus, and to give a legitimization to the decisions so he can quantify his circumstance and choose dispassionately on these decisions by featuring the powerful ends contrasted with those which are less so.

In the same vein, Roy also proposed the following definition: "*decision support is the activity of the person who, based on clearly explained but not necessarily clearly formalized models, helps to* *obtain answers to the questions asked by a participant in a decision-making process, elements that contribute to enlightening the decision and normally prescribe, or simply encourage, a behaviour likely to increase the coherence between the evolution of a process on the one hand, and the objectives and the system of values at the service of which this participant finds himself placed on the other hand*" (Bernard Roy, 1993).

1.2.1 The decision process

According to Chakhar et al, "The decision support activity revolves around a decision process which is a set of activities triggered by a stimulus and leading to a specific action commitment"(Chakhar et al., 2005). The decision process can be considered as a way from the information to the decision methodology. The writing concerning the ideas of the distinctive decision measures is tremendous, however, the most generally dispersed interaction is that of Simon(Mintzberg & Simon, 1977). We additionally discover different cycles, for example, the one proposed by(Mintzberg et al., 1976), or the one proposed by (Tsoukiàs, 2008).

a) The Simon model

Simon proposes the IDC (Intelligence, Modelling, Choice) decision process. This process has three main phases (Edwards & Turban, 1996; Pomerol, 1990; Power, 2002) It is considered to be the most famous model of decision-making processes available in the literature. It is shown in Figure 2 (M.ALNAFIE, 2016; Mintzberg & Simon, 1977)

1. Information. This comprises of deciding the arrangement of information identified with the decision circumstance.
2. Design. In this stage, the various choices that make up the arrangement of potential outcomes are created and the various arrangements are planned.
3. Choice. This stage permits the arrangement of potential outcomes to be limited to the subset of potential outcomes chosen and which will indeed be the arrangement.

A 4th step is usually added to control the implementation of the decision and the possible exercise of corrective actions (feedback).

"*This stage prompts the suggestion of an answer fitting to the model. It can prompt the reactivation of one of the three past stages or, unexpectedly, to the approval of the solution. After the choice, and to the extent that the decision is essential for a unique interaction, the "review" stage appears to be critical to us. New important data can impact either choice or even change it totally. Intelligent criticism can address numerous missteps and, over the span of a decision-making measure, it prompts exhibitions comparable to confounded techniques without input. This stage addresses the arrival of the decision support cycle to the real world. The last proposal should decipher the outcome given by the assessment model into the ordinary language of the customer and the decision cycle in which he is included.* "(Adla, 2010).

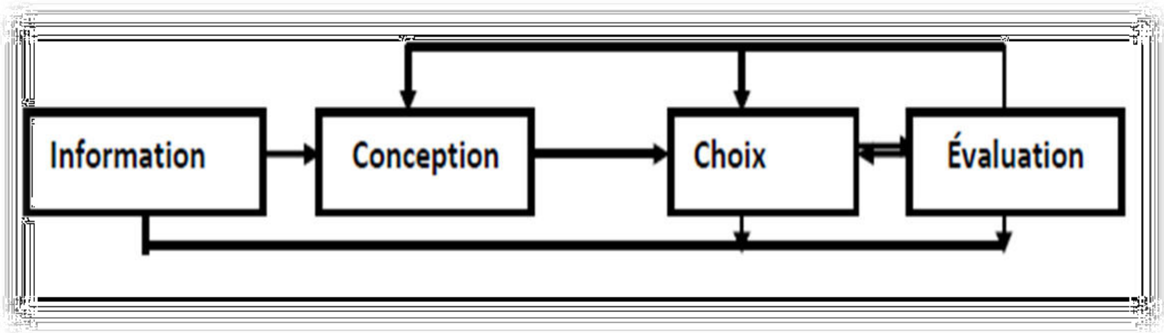


Figure 2 The decision-making process according to Simon

b) The Mintzberg et al. model,

This decision-making process contains several activities grouped into three basic phases (Chakhar et al., 2005):

1. Identification of the decision situation.
2. Development of possible solutions.
3. Selection of a solution to implement.

c) Tsoukias' model

Tsoukias introduced the concept of decision support process as an extension to the decision process. For the author, the decision support process is subdivided into three phases (Chakhar et al., 2005):

- Representation of the problem.
- Problem formulation.
- Evaluation.

1.2.2 Stakeholders in the Decision Support Process

The decision support measure includes a few members or actors. We recognize two fundamental ones: the analyst and the decision-maker. All things considered, different actors might be engaged with different limits. The investigation of the various actors (typology, objectives, interactions, etc.) is a significant angle to concentrate on examining a decision-making measure. Prior to portraying them, we will give Roy's definition.

According to Roy: "An individual or group of individuals is an actor in a decision-making process if, through his or her value system, whether at the first level because of the intentions of this individual or group of individuals or at the second level because of the way in which he or she involves other individuals, he or she directly or indirectly influences the decision" (B. Roy, 1986).

In a decision-making measure, it is conceivable to characterize the accompanying fundamental actors(Bernard Roy & Bouyssou, 1993):

- The decision-maker: the individual (group of individuals) helped by the decision help and who is assisted with bettering express their inclinations in a given circumstance.
- The investigator: is an individual or group of individuals whose job is to build up an arrangement of inclinations, to characterize the decision help model, to exploit it to acquire answers and to set up suggestions to prompt the decision-maker on potential arrangements.
- Negotiator: commanded by a decision-maker to affirm the last's situation in an arrangement and to look for a trade-off arrangement.
- The authority (judge): mediates by replacing the actors in the quest for a compromise action.

1.2.3 Decision models

From a theoretical point of view, we can distinguish three main types of decision-making models within an organization (Simon, 1983):

- the judicious or classical model, where man is viewed as completely informed to settle on an ideal decision;
- the political model, where decisions are somewhat the object of exchanges between gatherings;
- the mental model, where optimality is haggled to reach, as per Simon, the principle of limited sanity, a fairly palatable decision.

1.2.4 Typology of decisions

Decisions taken within the organization can be hierarchically classified according to their level, their deadline, their purpose or their nature. The following classifications can be found:

[a] According on the level of the decision

Kast differentiates three levels of decision according to the hierarchy in the decision structure: the planning level (top management); the steering level (management); the operational level (operations management) (Kast, 2002).

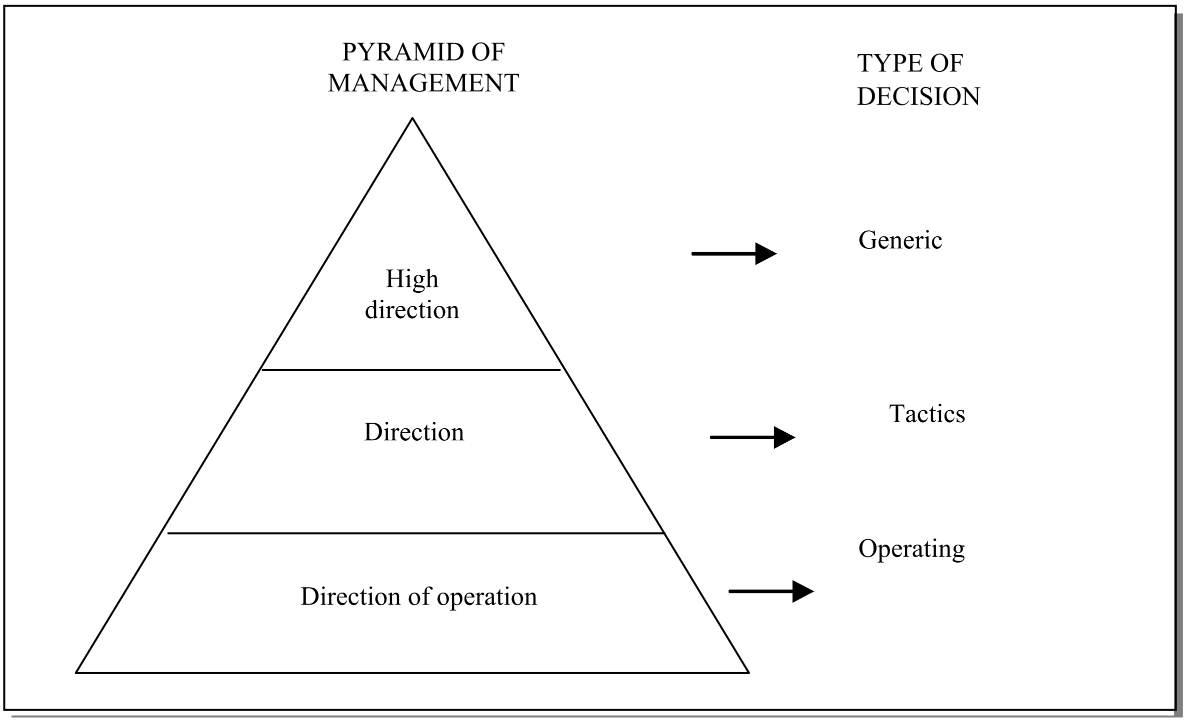


Figure 3 Decision levels (Kast, 2002)

[b] According to the deadline of the decision

Igor Ansoff proposed a classification of decisions in three categories (Ansoff & Waquet, 1989):

- The short-term decision: it's a decision that influences the future for a brief period. From a couple of days to a couple of months (by any large not over one year), for instance, the decision of a periodic provider for a little amount of a spare part.
- The medium-term decision: it's a decision that influences the future more than one year or more, for instance, the substitution of a machine in a factory.
- Long-term decisions: it's a decision that influences the organization's future throughout a significant stretch of time (5 years, 10 years, considerably more). They are regularly key, for instance, the establishment of a factory in a district.

[c] According to the purpose of the decision

Ansoff defines the following classification (Ansoff & Waquet, 1989):

- Strategic decisions: these are major, fundamental decisions that include the organization's future in the medium and long haul. They concern the organization's relations with its current circumstance (for instance, the decision to deliver another tourism product item for a specific customer base). It must be painstakingly thought out, it connects with the future. This kind of decision is the obligation of the board.

- Tactical decisions: These are made at the centre level of the organization's hierarchy. Decisions at this level are the board decisions that guarantee the acknowledgement of key decisions in the medium and present moment, for instance, the decision of a supplier after approval of the crude material request.

- The operational decision: It is taken at the lower part of the various levelled pyramid of the organization, and comprises in guaranteeing the current and steady working of the organization. It's anything but a "daily practice" decision and by and large, don't represent specific trouble. For instance, changing a provider if there should be an occurrence of inaccessibility of an product.

[d] According to the nature of the decision variables

Simon proposed another classification (Mintzberg & Simon, 1977):

- Programmable decisions: these are not difficult to settle on decisions that include quantitative and limited data. It is then simple to formalize the decision by fostering a programmed execution system.
- Non-programmable decisions: these are troublesome decisions for which the information is qualitative and various. It is hard to include them in a strategy or numerical model. They react to another occasion. Clearly, this sort of decision is more costly on schedule and budget.

With the continual growth of medical knowledge and therefore the arrival of latest diseases, diagnosis has become complex. Classical methods of medical investigation have shown their limits. Since then, AI was put to use within the medical field round the 1970s (E.H, 1976), but without considerable impact, nevertheless, tons of labor was administered and contributed to the progress of medical research. round the 1990s ,a stage was reached with the looks of doctor systems and medical decision support(Edwards & Turban, 1996; Szolovits et al., 1988), taking advantage of the evolution of computing with the arrival of medical data warehouses and new information technologies. Medical decision support then imposed itself within the current practice then became a serious axis of medical informatics. We present within the following section the medical decision support, where we note very great progress especially by many works associated with the diagnosis and therefore the treatment of the diseases like diabetes, asthma et al. (Jha et al., 2013; Marling et al., 2008; R. Sivakumar, 2007; Sefion et al., 2003).

1.3 Medical decision support

Medical data and knowledge became more and more numerous and sophisticated. The physician cannot memorize all the medical knowledge he needs in his daily practice. As a result, he must be better given the means to hold out these tasks associated with patient management. Among these tools are decision support systems that are occupying an outsized space in health research for several years. In fact, in medicine, the choice is considered because the center of the medical act.

the method of decision making consists, among other things, in making a diagnosis, a therapy, a prognosis. This medical act is centered on the reasoning that the clinician must adopt so as to succeed in a thoughtful action. This reasoning is meant to support this act. This involves the utilization of varied data, information, knowledge and clinical reasoning methodologies. we'll review some basic notions of clinical reasoning that allow us to know the sector we are investigating.

The field of *Interactive Decision Support Systems* (IDSS) is extremely tremendous. A couple of creators have proposed generally complete proclamations of the state of the art (Davis et al., 1986; Lévine and Pomerol, 1990). This section initially presents the thought of decision making just as certain definitions identified with it. This show doesn't profess to be comprehensive however just means to present at least components vital for the introduction of IDSS. From there on, the various ideas connected to IDSSs will be introduced just as the principal boundaries that have prevented their prosperity.

1.3.1 The clinical reasoning

Clinical reasoning is summarized by (Pelaccia et al., 2011), and (Kassirer, 2010), as follows: "The process of clinical reasoning is analytical (hypothetico-deductive models), non-analytical (recognition of similarity with a previously seen case) or a combination of both. The analytical model is considered to be a sequence of steps that contain first the generation of diagnostic hypotheses and then the search for clinical information to confirm or invalidate these hypotheses. The clinical information gathered can furthermore deduce new hypotheses. This process is carried out until the diagnosis is confirmed or eliminated. The non-analytical model is also considered to be the recognition of a clinical situation stored in the memory that corresponds to the clinical experience. This clinical experience contributes to the generation of hypotheses, but this interaction is not always positive, the recall of a clinical situation can sometimes disrupt a goal, but can also complement the analysis of the observed signs" (Kassirer, 2010; Pelaccia et al., 2011).

For our methodology, we utilized a non-analytical model to consider the thinking of the doctor when confronted with a neurotic circumstance. The doctor frequently utilizes his ability (thinking) and more or less comparative circumstances previously experienced (memory). Hence, the doctor's clinical thinking includes the components referenced in Figure 4, which are unequivocal in the goal of the present clinical circumstance that emerges before

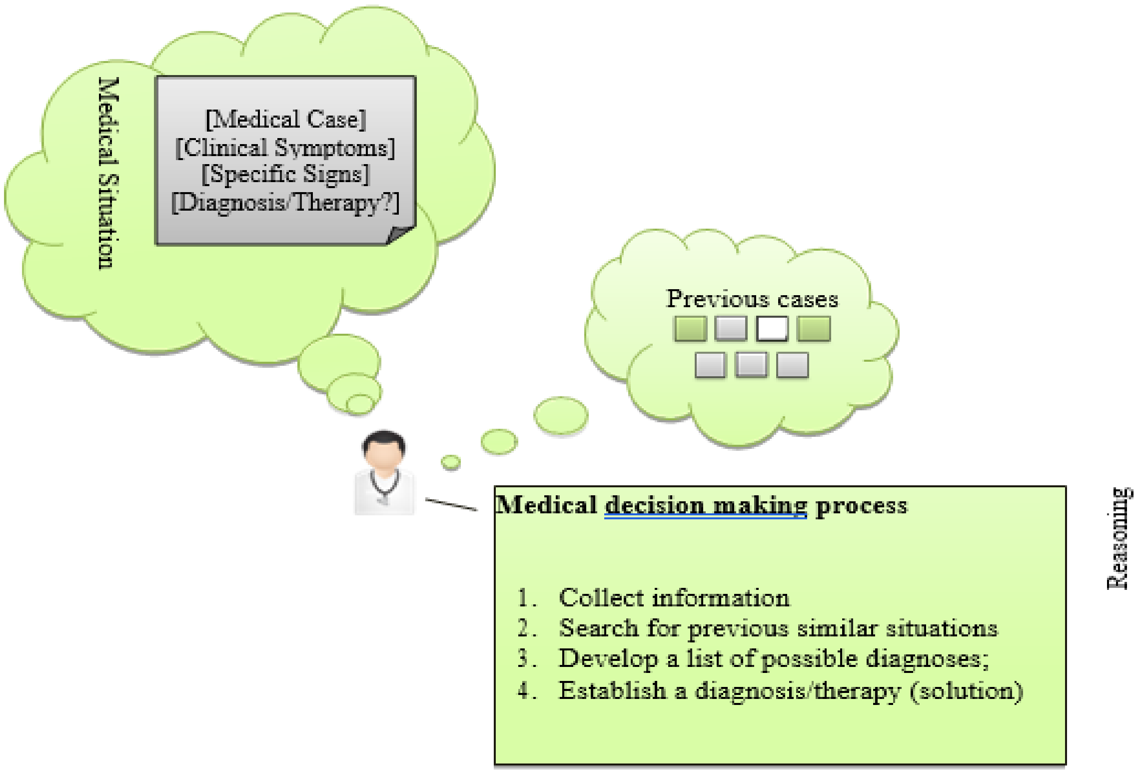


Figure 4 clinical reasoning

1.3.2 The decision in situation

An important notion in decision theory is that of the decision in situation (Guarnelli & Lebraty, 2014). The integration of the concept of decision situation will be the foundation establishing the current of "decision in situation" (Guarnelli & Lebraty, 2014; Klein & Sullivan, 2001; Rasmussen, 1986). In this vein, "the analysis of a decision must integrate the context in which it is made. The decision model will focus on the recognition, by the decision-maker, of the decision-making situation

(Recognition-Primed Decision Model)" (Lebraty, 2006). The idea of this approach is that it no longer studies the cognitive process independently of the context in which it takes place. This approach proposes that the decision should not be executed outside its context, that is to say outside the rules in which the situation is described (James Reason, 1990). Lebraty then defines the context as follows: "The set of elements, perceived by the decision-maker, which exert a constraint on the managed task. Thus, the context is both task-dependent and subjective. It can be seen as the explicit and tacit knowledge that enables the decision-maker to apply his or her skills in a given situation" (Lebraty, 2006).

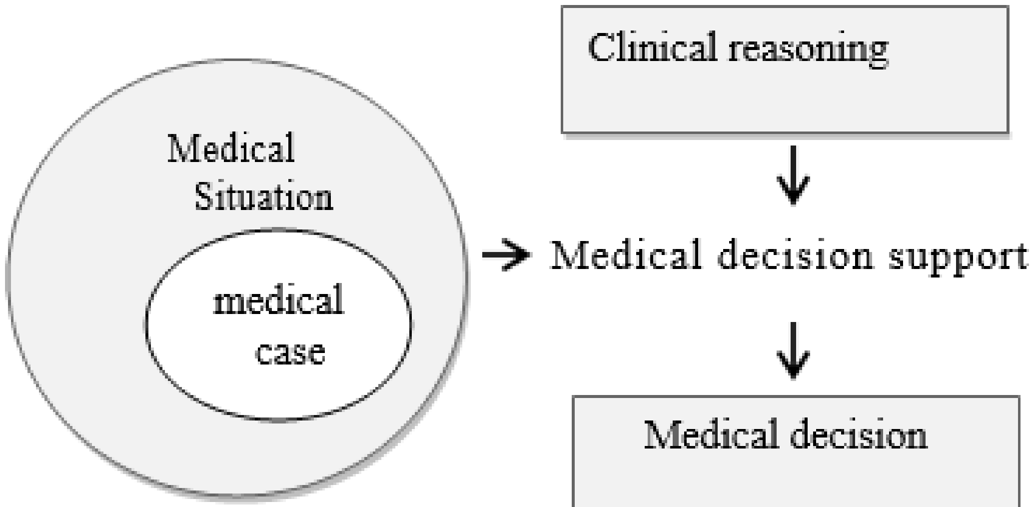


Figure 5 Elements contributing to the medical decision

1.3.3 The medical decision

When making a decision, the doctor should act without knowing all the information about a patient and obviously all the particular information about the circumstance. The doctor frequently needs assistance to build up a quality decision following a clinical diagnosis. Accordingly, the clinical diagnosis turns into the essential to any decision. This interaction of acknowledgment and arrangement finding is long and sensitive. This has prompted the plan and advancement of systems to support clinical decision. This is regularly called: clinical decision support. On the off chance that we need to characterize the clinical decision support, we can say: "it is the arrangement of strategies and instruments of information preparing permitting to help an interaction of setting up a decision identifying with a clinical circumstance". This interaction intends to help a medical care specialist take sufficient measures in the administration of patients. Be that as it may, this help is restrictive on a clinical diagnosis before any decision being made by the doctor. It's anything but an issue of getting information through a noticeable setting. Sournia characterizes clinical diagnosis as follows: *"Scholarly cycle by which an individual of a clinical calling recognizes the sickness of someone else submitted to his assessment, from the indications and signs that the last presents, and with the assistance of conceivable correlative examinations"* (Soumia, 1995) .

Indeed, a clinical diagnosis is a troublesome assignment to complete in light of the fact that it depends on the doctor's capacity to reason, to observe the side effects. This diagnosis conditions the clinical decision. This progression is even more troublesome in light of the data utilized, which might be corrupted by vulnerability and different types of defect. This vulnerability can emerge out of different sources: blunder in the information, vagueness in the portrayal of the information, vulnerability about the connections between the different information, and so forth These challenges have prompted the plan and advancement of analytic help systems to help doctors in the elaboration of their determinations and the medicine of sufficient treatments. A clinical diagnosis is in this way the demonstration of partner the name of at least one illnesses with noticed signs (history, manifestations) on account of a patient.

(a) The doctor notices the symptoms of a patient. In view of these indications, he/she forms introductory analytic hypotheses.

(b) He directs an underlying assessment of the patient, which permits him to build the level of certainty for specific theories and neglect it for other people. Simultaneously, the doctor poses the patient inquiries whose answers are helpful to affirm or dismiss an at first settled speculation.

Assuming the case stays vague after these procedures, the doctor looks for another wellspring of data that can give extra information to dispense with the equivocalness. This is normally given through extra assessments (analyses, X-rays, and so on) Regularly, these extra investigations complete the data in his ownership. In the event that the doctor actually can't build up a total and solid diagnosis, the last advance is to consider an information base of comparative cases treated in the past to set up a correspondence with the current case.

Subsequently, it has been feasible to foster systems fixated on medical activity, permitting clinicians to profit with the conceivable outcomes offered by software engineering and data handling techniques, to improve their insight, their decisions, and to control their exercises. These systems are called: Computer-Aided Diagnosis systems (CADs).

1.4 Computer-Aided Diagnosis systems (CADs)

Expert systems were at the origin of the first CADs. Subsequently, clinicians have shown great interest in these systems, in their routine practices in medical settings (medical office, laboratory, hospital and others) (Osheroff et al., 2009) :

- to decide on certain routine tasks ;
- to alert clinicians of potential problems ;
- or to suggest examinations to clinicians.

The literature is very varied in definitions and names for decision support systems (Alter, 1980; JL McKenney, 1971; Keen, 1978). Some authors emphasize the type of problem or functionality of the system in question, others emphasize the components or processes they use. For a broader reading on IDSSs.

In the medical field, IDSSs are also called CADs (Séroussi & Bouaud, 2014), others call them IDSSM (Ltifi et al., 2014). In our work we use the name CADs, with the precision that the interactivity aspect is strongly present as soon as the user is assured of being able to carry out the following operations that allow him to interact with the system either to introduce data, launch processes or validate results returned by the system.

Until the early 1990s, the use of CADs was limited to the hospital environment. In the early 2000s, their use went beyond the hospital setting thanks to the development of Information and Communication Technologies (ICT).

Nowadays, they cover almost all medical activities of diagnosis, therapy, prognosis, etc.

1.4.1 Definitions

Definition 1.

Serroussi and Bouaud define Computer-Aided Diagnosis systems(CADs) as computer applications whose purpose is to provide clinicians, in a timely manner and place, with information describing a patient's clinical situation, as well as knowledge appropriate to that situation that is properly filtered and presented to improve the quality of care and health of patients" (Séroussi & Bouaud, 2014).

Berner also states that "to improve the quality of care and the health of patients, information must also be: properly filtered and presented; provided in a timely manner and in a useful place"(Moreno, 2015).

Definition 2.

Greenes defines medical decision support as: "the use of information and communication technologies providing knowledge relevant to a patient's health care and well-being" (Greenes, 2014; Moreno, 2015).

Bates et al. specify that relevant knowledge is "passive and active information, reference, reminders, alerts and recommendations" (Bates et al., 2003; Moreno, 2015).

1.4.2 The objectives of CADs

The principal objectives of an CADs are to:

- to give information and data in line with the clinician during the different demonstrative and therapeutic research activities

- to propose a diagnosis, a treatment, or a prognosis;
- t to alert at the right time to avoid adverse events.

Likewise, and all in all, it can intercede in different structures. We then, at that point have:

- help with documentation of care;
- online admittance to reference data
- management of complex protocols or processes.

1.4.3 The main functions of CADs

The most well-known decision support functions in Computer-Aided Diagnosis systems are alerting and reminding. In an ongoing climate, these functions are joined to observing devices to give quick alarms as the setting off condition happens. For instance, oxygen and circulatory strain checking in a difficult setting can alarm nurses if the patient's condition surpasses a set threshold. In an ongoing setting, a straightforward investigation of lab results or an email caution to the decision-maker is valuable decision support capacities. Some Computer-Aided Diagnosis systems can give picture acknowledgement and understanding capacities. These are incredibly helpful in circumstances where radiology reports can be interpreted and alerts can be generated to get the doctors consideration(What-when-how, n.d.).

Function	**Examples of clinical problems**
Alert	Based on laboratory results with different customizable levels
Diagnosis	Identify possible diagnosis based on history, physical, results and data entered.
Reminder	Remind practitioners of orders and their schedules
Notification	Non-compliance, risks, abnormal events and care periods
Suggestion	Medication adjustments, trends and current drug dosages

Interpretation	Guidelines for the current situation - test-lab schedule, care protocols
Prediction	Predicting outcomes based on certain independent variables
Assistance	Provide an alternative drug due to drug interaction or allergy
Critique	The use of a medical procedure based on applicable medical guidelines and the patient's medical history

Table 1 Decision support functions and examples of clinical problems(What-when-how, n.d.).

1.4.4 Structure of a CADs

Computer-Aided Diagnosis systems comprise of (Moreno, 2015):

- an information base worked from suggestions and standards of medicine;
- information models addressed by information portrayal formalisms;
- an inference motor utilizing thinking techniques to derive diagnostic, curative or prognostic decision support;
- an interface guaranteeing correspondence between the clinician and the system.

1.4.5 Typology of the CADs

In the wide range of systems or prototypes developed, the literature provides several approaches for their classifications. Moreno cites for example two types those based on knowledge or not (Moreno, 2015). We will only mention these two classifications as examples

a. According to the mode of intervention

These systems depend on transit they mediate in the decision process in general, i.e., how they help in the decision making.

- *Indirect decision support systems or report support systems.*

Admittance to important data is essential for the decision-making measure. Consequently, admittance to the aftereffects of biochemical examinations or counsel of the patient's medical document is circuitous guides to decision making. This guide is utilized to work with the doctor's appraisal of a circumstance. Data set systems concerning drugs and their communications are instances of systems that can intercede in medical decision. Be that as it may, this decision support has stayed at the exemplary phase of putting away and recovering data. These narrative systems don't have a thinking strategy all things considered however they should manage data sets.

- *Automatic reminder systems or alert systems.*

These systems remind the physician of errors to not be made or of important elements to be taken into account when making a choice. the assistance provided isn't an aid to reasoning or to the overall understanding of the patient's case, but rather a reminder providing useful and relevant information during a more or less simple clinical situation. Thus, as an example, a warning when describing the dosage of a drug can also be seen as a valuable aid choose. These systems don't really reasonable, but the help becomes more personalized insofar because the system takes into account the knowledge it's on things under consideration. The alerts are often of varied nature sort of a therapeutic protocol when pathology is recognized or simply provide the normal values of biological examinations.

- *Consulting systems*

Their purpose is to offer a specialist's opinion on a selected clinical situation, whether it's diagnostic or therapeutic. doctor systems are often classified during this category. These systems reason on defined medical situations and supply the user with conclusions argued consistent with the reasoning methods used. it's during this category that we note the foremost achievements in terms of decision support systems.

b. According to the knowledge-based (symbolic) representation

These systems emphasize the way they store their medical knowledge, which also influences their reasoning patterns. The knowledge domain contains the principles and relationships between the info written most frequently within the sort of "if-then" rules. These

CADs are composed of three parts: the knowledge domain, an inference engine and an interface to speak with the clinician user of the system. The inference engine uses the principles and therefore the patient data to infer "solutions"(Moreno, 2015).

c. According to the data-based (numerical) representation

These systems use AI through specific algorithms (genetic algorithms, neural networks). However, they cannot explain the reasons for their conclusions. *“These systems are not directly used for diagnosis, for reasons of reliability and liability. Nevertheless, they can be used for post-diagnosis“* (Moreno, 2015). We then find:

- ***Diagnosis support systems.***

These systems use several more or less complex ways to help the physician who requests them (Moreno, 2015):

- suggesting a set of possible diagnoses;
- prescribe complementary examinations such as imaging, biological analyses or others;
- show a therapeutic scheme to be followed to determine the responsible disease, following a preliminary diagnosis;
- produce information that can help in the follow-up of a pathology;
- Produce a medical summary for the management of chronic patients.

- ***Therapeutic decision support systems***

We can discover:

- *Prescription assistance systems*

The doctor endorses a posting of medication and hence the framework performs an assortment of checks (hypersensitivity, drug association, and so forth) through an information base of prescription and in this way the patient's medical record, to approve or not the medicine. In the event that issue is distinguished (cooperation, and so forth), the framework produces an alarm. These systems are simply planned to get the remedy of a given medication (Moreno, 2015).

- *Therapeutic strategy support systems*

They assist the doctor with choosing the appropriate medication to prescribe, by setting up a remedial routine that requirements observing over the long run.

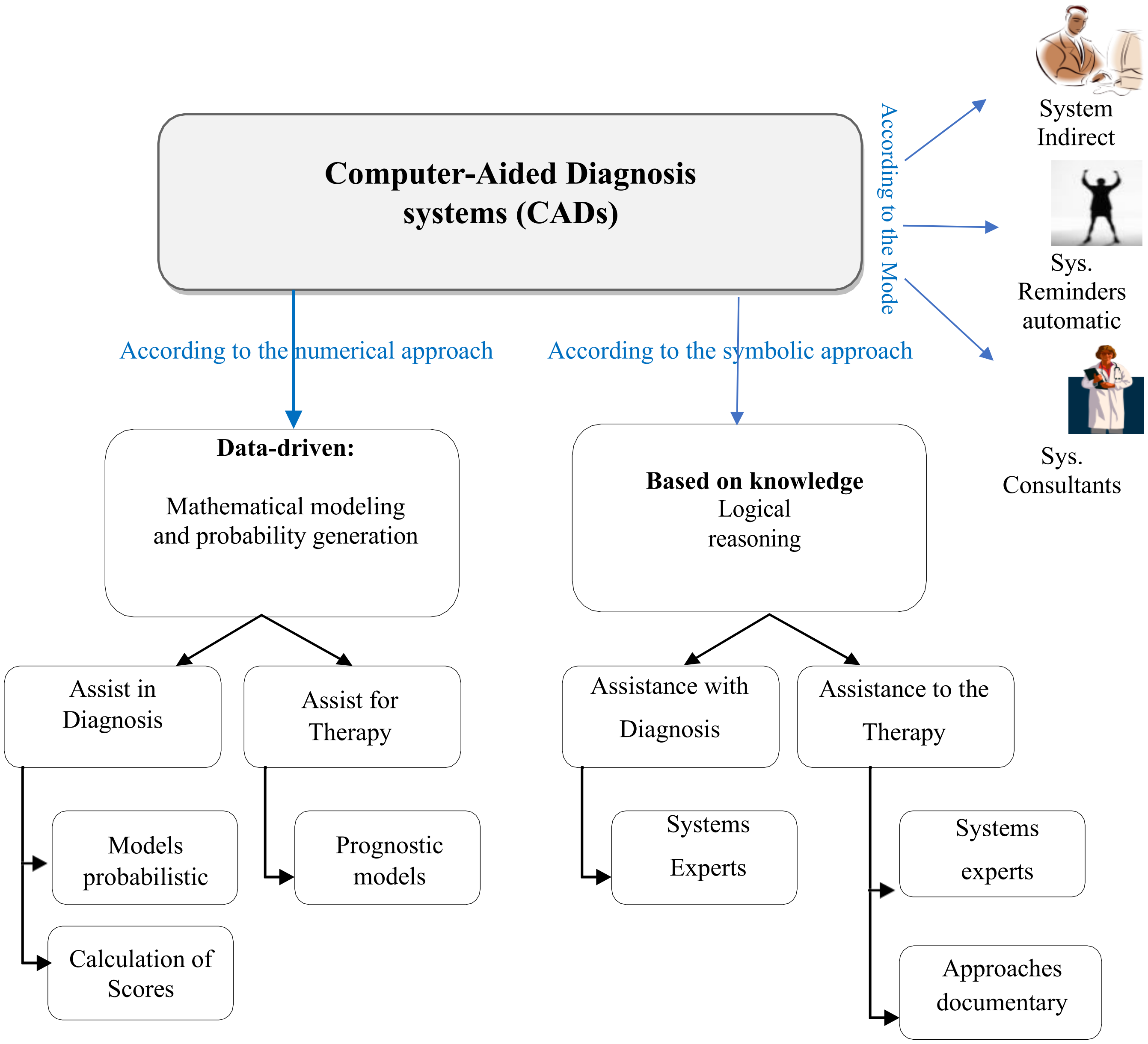


Figure 6 Typology of CADs according to the approaches used (Mansoul, 2020)

1.4.6 Components of CADs

Computer-Aided Diagnosis systems have been the subject of various accomplishments. For over twenty years, expert systems utilizing artificial intelligence (AI) techniques have been duplicating in medicine as in different fields of science and innovation. Prior to them, more conventional methodologies, in light of measurable or probabilistic strategies, had been generally evolved. Artificial intelligence techniques have empowered advances. On a technical level, they have permitted a significant subjective jump in the acknowledgement of complex systems. This advancement doesn't just concern medical applications yet, in addition, the management applications.

Artificial intelligence has subsequently prompted genuine information designing. It is portrayed by a methodology that makes a huge piece of cognitive psychology, the representation of symbolic information and the demonstrating of thinking measures. The figure underneath shows the construction of a medical decision support framework which incorporates:

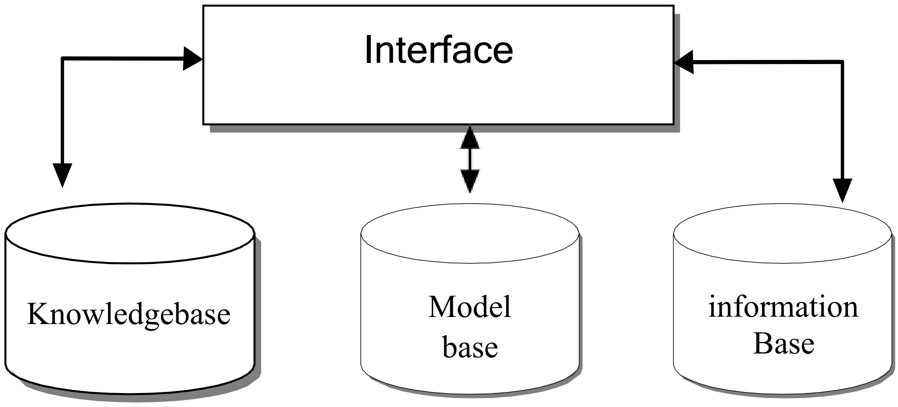


Figure 7 Structure of a CADs (Holtzman, 1989) .

– *The Information Base*

It accumulates information on the framework and ensures the accompanying capacities

- connect information from various sources;
- Search for information following queries;
- perform complex pursuits and information control for inquiries.

- *The model bases*

It explains the performance of the system. It consists of a set of models and a system for controlling them. The models can be: generational search tools, statistical models or others.

- *Knowledgebase*

It can be a fully-fledged and independent system that can provide additional and specific expertise to the system in place. The knowledge base gathers a set of knowledge on the problem domain.

- *The interface*

It ensures the communication between the system and the user.

1.4.6.1 Knowledge models

The knowledge base assembles all the knowledge of the field in the matter. This knowledge provided to be given to a system is of different kinds, we find, for instance, the translation of the consequences of biological examinations, anatomical, physio pathological, epidemiological, taxonomic (classification of diseases), pharmacological and therapeutic knowledge. Szolovits et al. propose to group the knowledge models utilized in medicine into three classifications (Szolovits et al., 1988):

(a) Empirical models.

Empirical knowledge refers to the knowledge of associations between diseases and signs. It can be provided by an expert or derived from the analysis of a database. This type of knowledge is very often used in expert systems. The best example of this type of knowledge and its implementation is certainly the MYCIN system (Shortliffe, 1976)using knowledge rules developed empirically by experts. Example of such a rule:

If color_urine="red" then patient="high risk

(b) Physiological and pathophysiological models.

This type of knowledge allows for deeper reasoning that describes, through relationships with clear semantics, the mechanisms underlying disease processes. Explanations based on causal knowledge are easier to understand. Causal knowledge is used to identify pathophysiological states. Other knowledge is used to classify the case according to previously confirmed or refuted states. The latter type of knowledge, applied to identified states and not to baseline data, is used at a higher level of abstraction than causal rules. Its purpose is to produce diagnostic and prognostic conclusions (Degoulet & Fieschi, 1991).

1.4.6.2 Knowledge representation formalisms.

The most commonly used formalisms in computer systems are production rules and structured objects or frames.

- *The production rules.*

They permit to just address knowledge that is normally communicated by conditional sentences, for instance:

IF blood_sugar_level >= 126 g/l THEN "the patient has a glucose level"

The knowledge expressed in this declarative way presents the simplicity of expression and ease of comprehension linked to its syntax.

Numerous systems, the most popular of which is MYCIN, utilize this method of knowledge representation and acquire fascinating performances. Two procedures for utilizing these rules can be carried out. The information-driven technique, called "Forward chaining", utilizing every one of the principles to reason all that is deducible. The procedure directed by the objective, called "backward chaining", from a proposition of an objective to reach, there is the development of every single possible way.

- *Structured objects (frames).*

Structured objects are largely ideas that present themselves to the mind. Distinctive knowledge and properties are appended to each object. An article construction can be addressed as a network of nodes and relations. It is additionally conceivable to characterize joins with specified semantics: relations among classes and instances, or among sets and subsets.

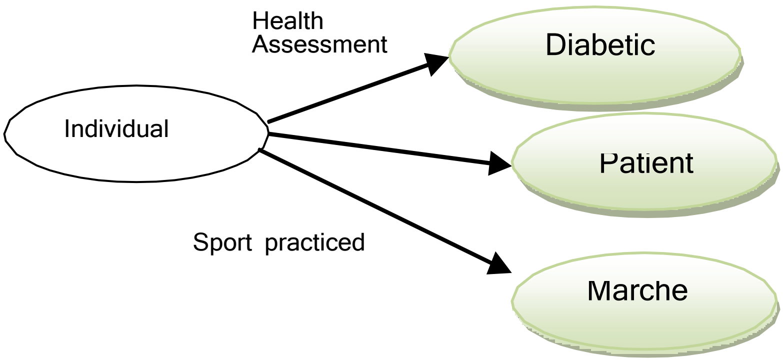


Figure 8 Example of the representation of the person class in a medical application.

At this level, we can oppose two types of knowledge, static knowledge and dynamic knowledge. Static knowledge corresponds to the definition of concepts. The dynamic knowledge describes the way to use the concepts and their properties in a reasoning where the empirical aspect of the rules is highlighted.

1.4.6.3 Methods of reasoning

The methods of problem solving and reasoning are very varied and can be implemented on the different knowledge models. Thus, the following types of reasoning can be used:

- Deductive reasoning, which deals with categorical data or uncertain and/or imprecise data and which implements the principle of logical implication or one of its generalizations.
- Hypothetico-deductive reasoning, or a generalization of reasoning by the absurd (by refutation), makes it possible to focus the search for a solution to a given problem.
- Qualitative reasoning is used to express common sense knowledge.
- Inductive reasoning and reasoning by analogy are also used.

This reasoning can be used to solve problems where all possible situations are enumerated a priori, as well as to solve problems where this enumeration is not possible.

1.4.7 Medical decision support methodologies:

1.4.7.1 Numerical approach:

approach, based mainly on the implementation of numerical algorithms (such as discriminant analysis or Bayes' theorem) was historically the first one used in decision support systems (Bruland et al., 2010).

1.4.7.2 Discriminant analysis and statistical methods

These methods are applied to a sample of cases (whose diagnosis is known, for example) to determine the discriminant function. Schematically, if we suppose that we are trying to discriminate sick subjects from non-sick subjects, we can say that it is a question, in a p-dimensional space corresponding to the variables describing the patients, of finding the plane which separates as well as possible (in the sense of a certain criterion) the points corresponding to the sick subjects and the points corresponding to the healthy subjects. This function obtained is tested on another sample of data in order to evaluate its validity. Many methods have been proposed and applied in different medical fields (Bellazzi & Zupan, 2008; Kashiyarndi, 2010).

1.4.7.3 Bayesian systems

The Bayesian approach has led to many applications, among which the De-Dombal application on acute abdominal pain is one of the most significant. This system uses a Bayesian model to calculate the probabilities of conditions manifested by acute abdominal pain. Each patient is defined by 35 to 40 variables and the 7 known diagnostic categories of the system are appendicitis, diverticulosis, duodenal ulcer perforation, pancreatitis, small bowel obstruction and non-specific abdominal pain (De Dombal et al., 1972).

1.4.7.4 The artificial intelligence approaches

The importance of knowledge to perform tasks in an intelligent way is the subject of several achievements in artificial intelligence (Koton, 1988; Szolovits et al., 1988). The goal is to deduce new conclusions or solutions by formally using descriptions of real objects or entities represented in an adequate formalism, and which are well suited for the desired treatments. Two modes of representation are then used: the procedural representation for a knowledge if this one translates an algorithm. Otherwise, this knowledge is not formulated, this knowledge cannot be formulated algorithmically, and there it is a declarative representation. Therefore, before any processing, it is necessary to think about and choose a suitable mode of representation for the representation of the states of the system, and the representation of the knowledge used to produce the new states, of course by "derivation" or deduction (Koton, 1988; Szolovits et al., 1988)

Chapter 2

State of the art

Surveying the danger of malignancy in the thyroid with ultrasound (US) is essential in patients with nodules, as it can support choosing the individuals who ought to have a fine-needle aspiration (FNA) biopsy performed. Many examinations have analyzed whether the US qualities of thyroid nodules are helpful pointers of histological malignancy. Generally, these examinations have distinguished a few US features that are altogether more regular in malignant thyroid nodules which can be combined into a characterizing set to be utilized as a marker of a higher risk of malignancy. Notwithstanding these endeavors, none of these classifications has been broadly embraced around the world, and there are still conflicting recommendations from different institutions. Understanding the role and suitable usage of these systems could work with the powerful translation and communication of thyroid US discoveries among alluding doctors and radiologists. In this chapter, first we lay out the significant US characterization scoring systems of thyroid nodules(TI-RADS),and secondly we present related work to our study we distributed over the most recent couple of years.

2.1 Introduction:

A thyroid nodule is defined by the American Thyroid Association (ATA) as "*a discrete lesion within the thyroid gland that is radiologically distinct from the surrounding thyroid parenchyma*"(E.H, 1976)(Cooper et al., 2009).

Thyroid nodules are very common in the general population, and their prevalence is dependent on the identification method used, with a high prevalence found in ultrasound (US) examination, ranging from 20% to 76% in the adult population(Periakaruppan et al., 2018). Non-palpable nodules detected on US or on other imaging examinations are called "thyroid incidentalomas" or "incidentally discovered nodules".

Thyroid nodules are more frequent in females, with an incidence 4 times higher in women than in men (Iqbal et al., 2005). Thyroid nodules may determine gland dysfunction and compressive symptoms due to mass effect, but the main concern is to rule out their malignancy.

US exam is a safe, non-invasive, and fast imaging technique: it is sufficiently sensitive for detecting thyroid nodules and identifying suspicious features and can be used to plan further investigation and management decisions

2.2 Ti-rads

The related studies significant to our work will be discussed in the following two main point bellow

Horvath (Horvath et al., 2009) was the first to propose TI-RADS as a method to stratify the estimated risk of cancer in thyroid nodules and select those nodules needing to undergo FNA. features considered by this classification include echogenicity, microcalcifications, shape, irregular margins, peripheral halo, and presence of suspicious lymph nodes. TI-RADS includes 10 US patterns combined

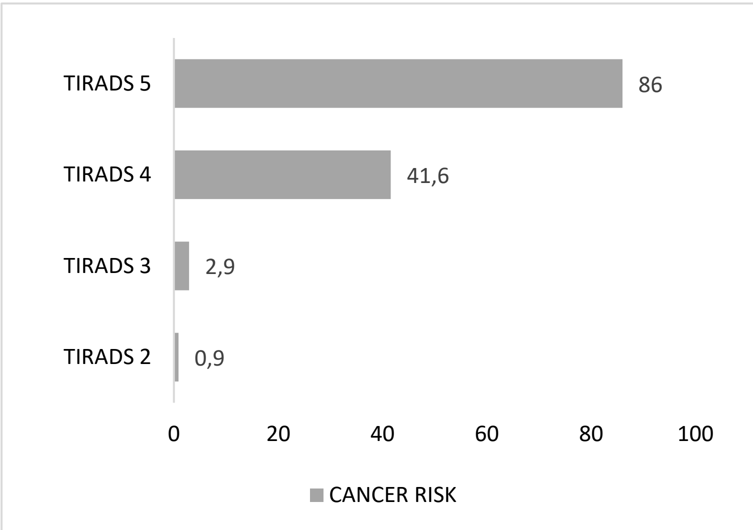


Table 2 TIRADS score with respective cancer risk %

into categories with the increasing risk of malignancy and nodules classified as TI-RADS score 2 to 5 (Horvath et al., 2009). the risk of malignancy rises in parallel with the increase of the number of suspicious US features and with the lack of benign findings.

2.3 American College of Radiology (ACR)-TI-RADS

ACR proposed another version of TI-RADS (Tessler et al., 2017) in order to identify the most clinically significant malignancies and decrease the number of FNAs on benign nodules.

This classification is not a pattern-based approach but is based on the assessment of different US features of thyroid nodules: composition, echogenicity, shape, margin, and echogenic foci; each of these features is associated with a score ranging from 0 to 3 points.

The sum of the assigned points defines the risk of malignancies according to 5 grades, with each grade corresponding to benign, minimally suspicious, moderately suspicious, or highly suspicious for malignancy.

The main goal of ACR TI-RADS is to balance the benefit of detecting clinically significant malignancies against the risk and cost of submitting benign nodules or indolent and non-aggressive tumors to invasive investigations and treatment. The indications for US follow-up aim at reducing the eventuality that significant lesions remain undetected over time.

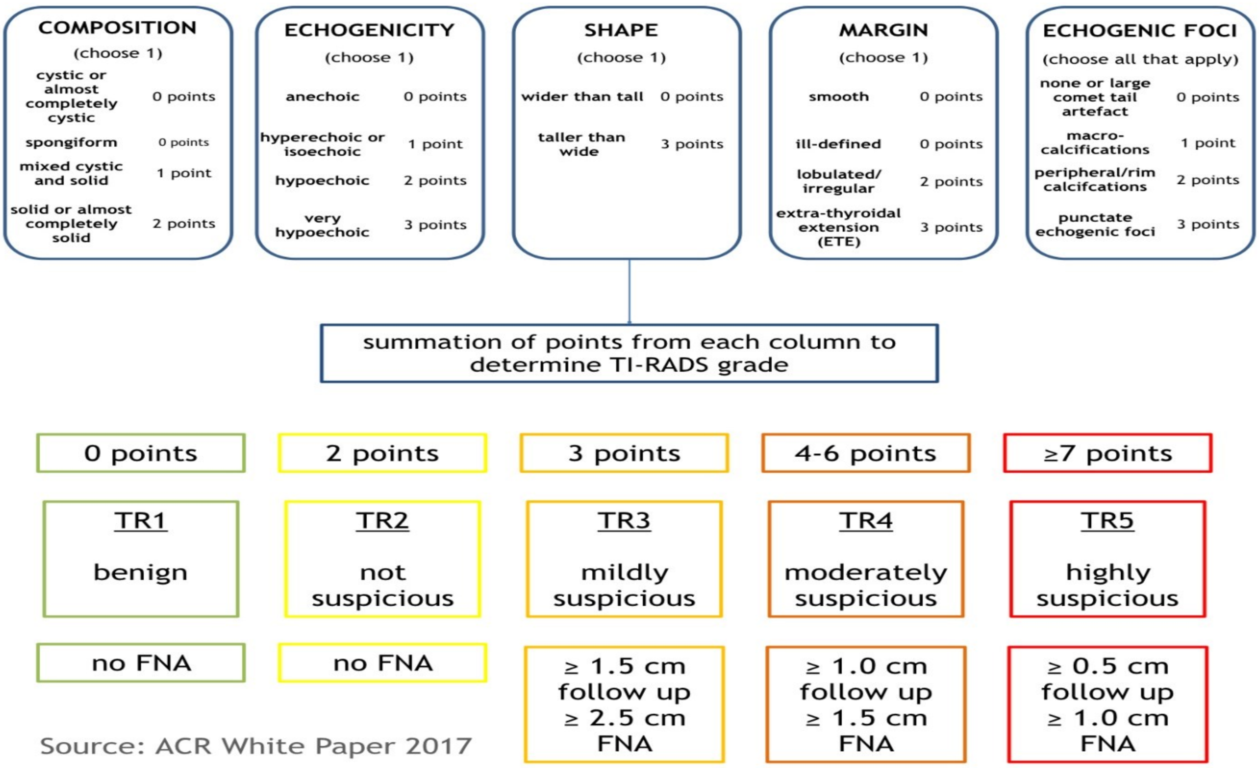


Figure 9 ACR-TI-RADS-scoring-system-diagram

2.4 European (EU)-TI-RADS

European (EU)-TI-RADS is a classification system first proposed by (G. Russ et al., 2011), and has been subsequently modified into an easier-to-use version, validated in a large prospective proposed by (Gilles Russ et al., 2013) and finally published as a European guideline as (Gilles Russ et al., 2017).

The latest version of EU-TI-RADS consists of five categories, each which is scored in correspondence to features from the US examination:

Category	US features	Malignanc risk, %
EU-TIRADS 1: normal	No nodules	None
EU-TIRADS 2: benign	Pure cyst Entirely spongiform	≅0
EU-TIRADS 3: low risk	Ovoid, smooth isoechoic/hyperechoic No features of high suspicion	2–4
EU-TIRADS 4: intermediate risk	Ovoid, smooth, mildly hypoechoic No features of high suspicion	6–17
EU-TIRADS 5: high risk	At least 1 of the following features of high suspicion: – Irregular shape – Irregular margins – Microcalcifications – Marked hypoechogenicity (and solid)	26–87

Figure 10 EU-TIRADS-categories-and-risk-of-malignancy

- Recommendations:

- **EU-TIRADS 1:** n/a
- **EU-TIRADS 2:** no FNA required (unless for therapeutic purpose / relieve compression)
- **EU-TIRADS 3:** >20 mm FNA/ low risk
- **EU-TIRADS 4:** >15 mm FNA/ intermediate risk
- **EU-TIRADS 5:** >10 mm FNA, <10 mm consider FNA or active surveillance/ high risk

2.5 Korean (K)-TI-RADS

K-TI-RADS was proposed in 2016 by (Shin et al., 2016). In this classification system, the malignancy risk estimated by US examination is not determined by a single US sign, but by a combination of them; the rationale is that any single US predictor is not sensitive and specific enough to determine the suspicion of malignancy. Based on US patterns including solidity, echogenicity, and suspicious US characteristics, thyroid nodules in the K-TI-RADS system are classified as high suspicion, intermediate suspicion, low suspicion, and benign

	Category	US feature	Malignancy risk, %	Calculated malignancy risk (%), overall (LV, HV)	Calculated sensitivity for malignancy (%), overall (LV, HV)	FNA[a]
5	High suspicion	Solid hypoechoic nodule with any of 3 suspicious US features[b]	>60	79.3 (60.9, 84.9)	51.3 (35.9, 56.7)	≥1 cm (>0.5 cm, selective)
4	Intermediate suspicion	Solid hypoechoic nodule without any of 3 suspicious US features[b] or Partially cystic or isohyperechoic nodule with any of 3 suspicious US features[b]	15–50	25.4 (15, 33.6)	29.5 (29.9, 29.4)	≥1 cm
3	Low suspicion	Partially cystic or isohyperechoic nodule without any of 3 suspicious US features[b]	3–15	7.8 (6, 10.3)[c]	19.2 (34.2, 13.9)	≥1.5 cm
2	Benign[d]	Spongiform	<3	0	0	≥2 cm
		Partially cystic nodule with comet tail artifact	<1	0	0	NA
		Pure cyst				
1	No nodule	-	-	-	-	NA

Figure 11 K-TI-RADS-scoring-system-diagram

2.6 Comparison between the different US classifications for thyroid nodules

It is critical to assess the risk of malignancy in the thyroid with US in order to properly identify those patients for whom FNA biopsy is a necessary priority. Many studies have investigated whether the US characteristics of thyroid nodules are useful indicators of histological malignancy. Overall, these investigations have identified a few US features that are significantly more frequent in malignant than in benign thyroid nodules, thus defining a set of US features at a higher risk of malignancy. The main features of these classifications are summarized on Table 3.

	US features								
Classification	*Echoge-nicity*	*Shape*	*Margins*	*Echogenic-foci (calcification)*	*Size*	*ECD features*	*Lymph-node evaluation*	*Categories*	*FNA recommendations*
TIRADS	√	√	√	√	×	Included	×	*TI-RADS1: normal thyroid gland* *TI-RADS 2: benign conditions* *TI-RADS 3: probably benign nodules* *TI-RADS 4: suspicious nodules* TI-RADS 5: malignant nodules	*FNA recommended from TI-RADS 3*
ACR–TIRADS	√	√	√	√	√	Included	×	*ACR-TI-RADS 1: benign* *ACR-TI-RADS 2: not suspicious* *ACR-TI-RADS 3: mildly suspicious* *ACR-TI-RADS 4: moderately suspicious* *ACR-TI-RADS 5: high suspicious*	*FNA recommended from mildly suspicious, according to on nodule size*
EU-TIRADS	√	√	√	√	×	*Not-*Included	√	*EU-TI-RADS 1: normal* *EU-TI-RADS 2: benign* *EU-TI-RADS 3: low risk* *EU-TI-RADS 4: intermediate risk* *EU-TI-RADS 5: high risk*	*FNA recommended considering US scoring + clinical setting*
K-TI-RADS	√	√	√	√	√	*Not-*Included	×	*K-TI-RADS 1: no nodule* *K-TI-RADS 2: benign* *K-TI-RADS 3: low suspicion* *K-TI-RADS 4: intermediate suspicion* *K-TIRADS 5: high suspicion*	*FNA recommended from the benign lesion, according to on nodule size*

Table 3 Comparison of existing and proposed classification systems

2.7 Related Work To Our Sutdy

Previous works on thyroid nodule classification can be grouped into two categories: deep learning-based and handcrafted-based methods(Nguyen et al., 2020). Before the appearance of deep learning-based methods, handcrafted-based feature extraction methods have been widely used for a long time. This is because they can be easily implemented with simple image-based systems. We construct a deep learning model for feature extraction and thyroid nodules classification from captured ultrasound images in deep learning-based methods. In (Sai Sundar et al., 2019), the authors proposed a classification framework based on Convolutional Neural Network (CNN). Here, they extracted the features from the inputted ultrasound thyroid nodule image using a pre-trained CNN. Then, they used the Support Vector Machine (SVM) method to classify the images into benign and malignant. The authors also constructed another CNN for image classification, and the features were extracted using transfer learning techniques (like VGG16-Net (Simonyan & Zisserman, 2015) or Inception-Net). In(Song et al., 2019), authors developed a multitask cascaded convolution neural network (MC-CNN) framework to exploit thyroid nodules' context information. Similarly, some authors used deep learning using the YOLOv2 neural network to classify the thyroid nodules.

Unlike the deep-learning-based methods mentioned above, handcrafted-based methods use several traditional feature extraction techniques to extract image features and a classifier to classify these features. However, these methods have low classification accuracy as they highly depend upon their feature extraction techniques. In(Chang et al., 2010), authors used textural features like Gray Level Co-occurrence Matrix (GLCM), Gray Level Run-Length Matrix (GLRLM), and Law's texture energy measures to obtain the features. These features are then classified using the standard SVM. Again, in(Sudarshan et al., 2016), authors used the Discrete Wavelet Transform (DWT) to locate the tumor region and to extract subtle information from isolated tumor regions for classification. The authors in (Ouyang et al., 2019) performed an analysis of linear and nonlinear classifiers for ultrasound images. They showed that both the methods give comparable (almost similar) accuracy. Another study that employed a handcrafted-based method is done by Raghavendra et al.(Raghavendra et al., 2017), where they used Segmentation-based Fractal Texture Analysis (SFTA) to extract the features.

It is evident from the above works that most of the handcrafted-based methods used textural properties of the ultrasound images. The classification system's performance depends on the extraction of the features and very little on the classier used. The most recent work(Shastri & Aditya, 2020) has proposed the use of the two descriptors: Histogram of Texture (HOT) and Pass Band - Discrete Cosine Transform (PB-DCT) with a feature selection technique called Discrimination Potentiality (DP), which captures the textural information in a better way. These descriptors overcome the only disadvantage that the handcrafted-based methods have: low classification accuracy.

Category	**Advantages**	**Disadvantages**
Handcrafted-based Methods	• Easy implementation • High-performance hardware not required	• Low accuracy
Deep learning-based Methods	• Use deep learning and transfer learning methods • Higher accuracy than handcrafted methods	• There is always room for improvement • High-performance hardware required. • Require more processing time
Used Methods (DP-HOT and DP-PB-DCT)	• Easy implementation • High-performance hardware not required • More accuracy due to texture exploiting descriptors	• DP-PB-DCT performance is low as compared to DP-HOT

Table 4 Comparison of existing and proposed classification systems

Chapter 3

Proposed Methods

This work proposes a two-stage thyroid nodules classification system. In the first stage, thyroid nodules are classified as benign-malignant, and in the second stage, benign nodules are further classified in TIRADS 2/TIRADS 3, and malignant nodules are further classified in TIRADS 4/TIRADS 5. We are using SVM to classify the nodules in their respective classes.

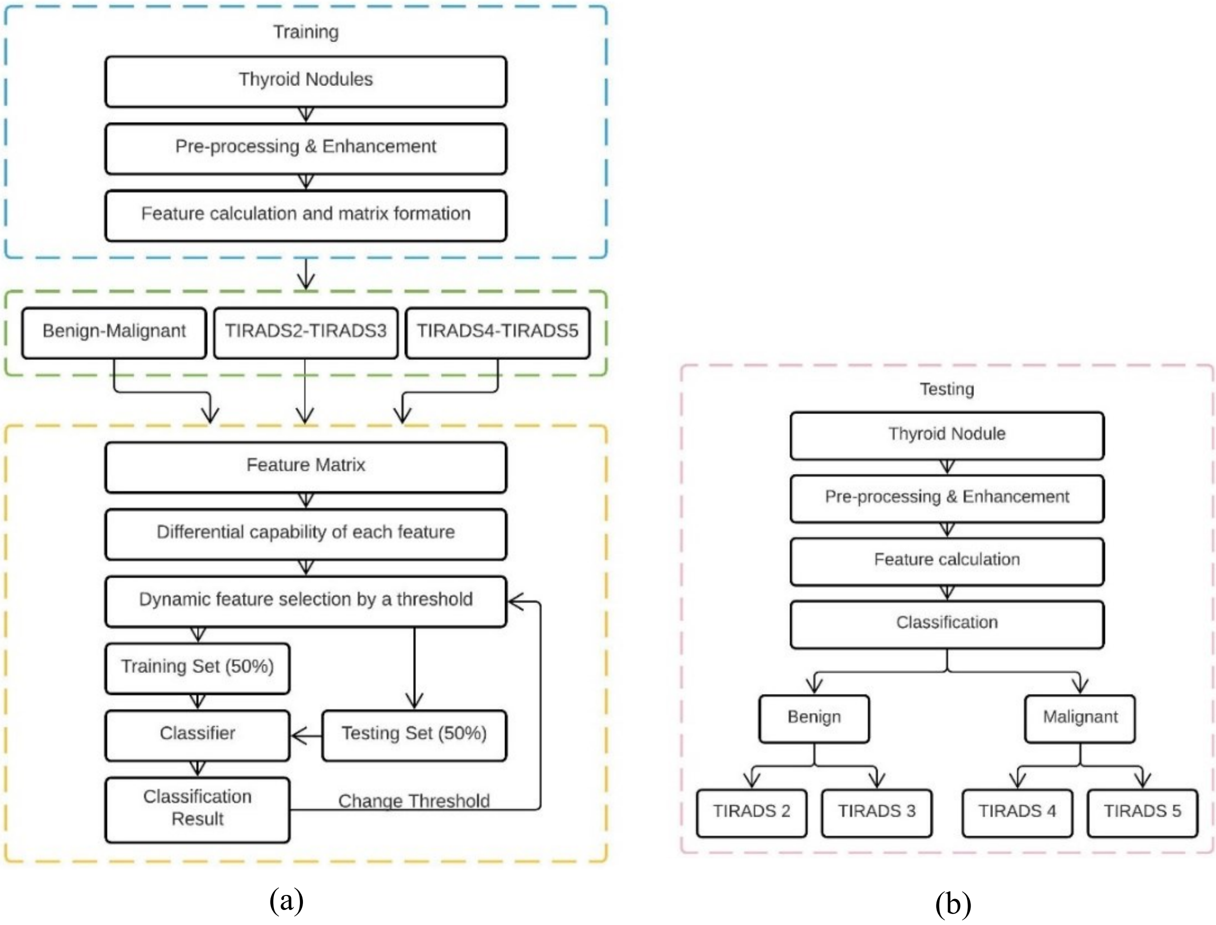


Figure 12 - Flow diagram of the proposed classification system; (a) training phase and (b) testing phase

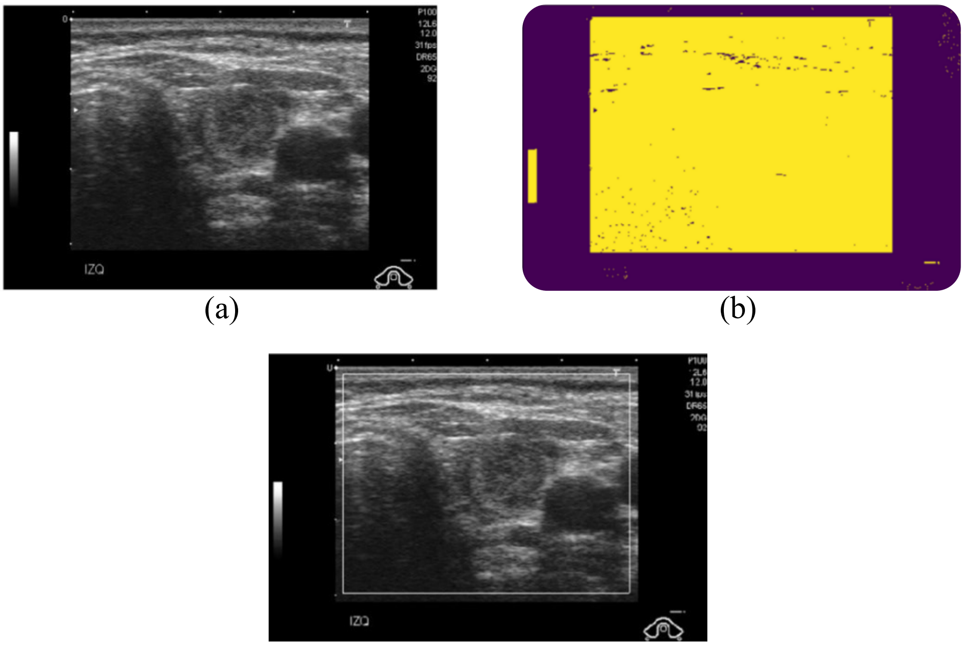
The framework of the proposed work for the training and testing phase is shown in Figure 12. Here, we first discuss image pre-processing and enhancement techniques. Thyroid nodules are pre-processed for illumination normalization and visibility enhancement of tumors and tissues. A two-stage adaptive histogram equalization enhancement technique is used here for texture enhancement of thyroid nodules. Second, we discuss the two feature extraction techniques, where features of thyroid nodules are extracted from enhanced images. Then, we discuss the feature selection technique used by us, and finally, we discuss the minority oversampling technique.

3.1 Pre-processing and Enhancement

3.1.1 Image Binarization

As shown in Figure 13 (a), the captured ultrasound thyroid images contain two main parts, i.e., the background (boundary parts with low illumination and some additional artifacts) and the thyroid region (the inner brighter part that captures the details of the thyroid region). It is easy to see that the background regions contain no information about whether an image contains benign or malignant cases of thyroid nodules. It also contains some artifact information added to an image as indicators for the radiologist, such as the patient information or capturing system configuration during the image acquisition process. Due to this reason, the background region should be removed before passing images to the primary classification system. As shown in Figure 13 (a), the thyroid region is typically displayed as the largest brighter region in the captured ultrasound thyroid image. Although several brighter regions exist in an ultrasound thyroid image, such as the illumination indicator and text for specifying capturing system configuration, these regions' size is much smaller than that of the thyroid region. We first performed an image binarization method to detect all brighter regions in the captured image using an optimal threshold value based on this observation.

Our study used a binarization method proposed by Otsu et al.(Cancer.Net, 2020), which takes an input image and performs binarization adaptively by selecting the most suitable threshold value. The result of this binarization step is given in Figure 13 (b) using the input image of Figure 13 (a). As shown in Figure 13 (b), although some brighter regions were detected, the thyroid region had the largest size. Finally, the detected thyroid region was determined by taking the bounding-box in the input image (in Figure 13 (a)) based on the selected region of Figure 13 (b). An example of a resultant image of this step is given in Figure 13 (c) using the input image of Figure 13 (a). As we can see from this example, the thyroid region was well localized using our localization method.



(a) (b)

(c)

Figure 13 - Example result of thyroid region detection algorithm. (a) an input ultrasound thyroid image; (b) the binarized image; (c) the final detection result

3.1.2 Image Normalization

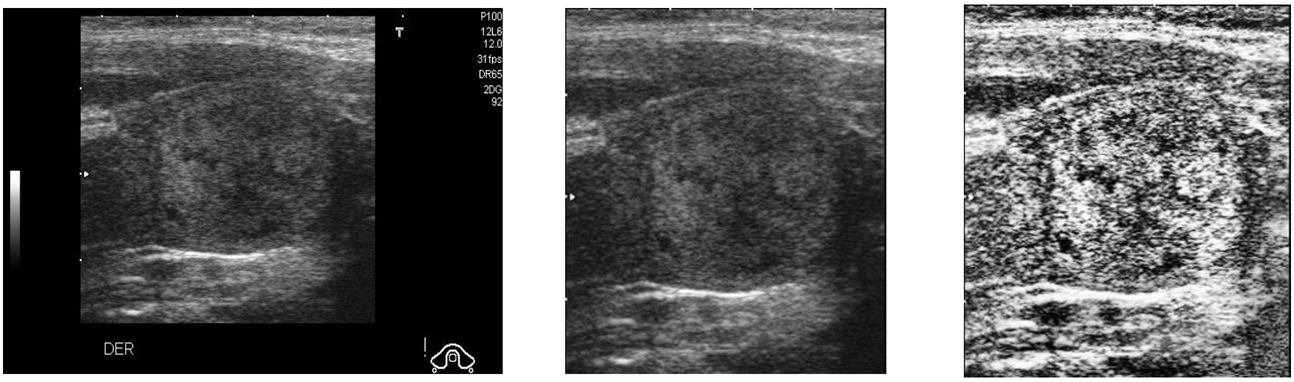
Then, we normalize the intensity of pixels of the thyroid nodule images because while capturing images, illumination conditions are usually not the same. So, the range of the gray level is different for different thyroid nodule images. Hence, we use a simple and the most commonly used normalization formula (eq.1), which normalizes pixels' intensity between 0 and 1 (Nguyen et al., 2020).

$$I'(x,y) = \frac{I(x,y) - \min(I)}{\max(I) - \min(I)} \quad \text{Eq.1}$$

where (x, y) is the pixel position, $I'(x, y)$ is the normalized pixel intensity, $I(x, y)$ is the actual pixel intensity, $\min(I)$ is the minimum intensity over all the pixels, and $\max(I)$ is the maximum intensity over all the pixels.

3.1.3 Image Enhancement

Next, we discuss tissue enhancement of thyroid nodules. Histogram Equalization is an image processing technique that adjusts the contrast of an image by using its histogram. To enhance the image's contrast, it spreads out the most frequent pixel intensity values or stretches out the intensity range of the image. By accomplishing this, histogram equalization allows the image's areas with lower contrast to gain a higher contrast.. As a result, if the region of interest in an image occupies only a small portion, it will not be enhanced appropriately during histogram equalization. This leads to more advanced techniques for enhancement, e.g., Adaptive Histogram Equalization (AHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Unsharp Masking (UM), Non-Linear Unsharp Masking (NLUM), Two-Stage Adaptive Histogram Equalization (TSAHE), etc.(Nguyen et al., 2019). CLAHE is more suitable for tissue enhancement in thyroid nodules(Chang et al., 2010). Since cancerous cells mostly develop in tissues and the HOT and the PB-DCT descriptors are strongly tied to tissue texture, we use a combination of CLAHE and TSAHE. We apply two stages of CLAHE on thyroid nodules in a cascaded order. Firstly, histogram equalization is applied to 8×8 sized blocks, followed by an application to 4×4 sized blocks. .Figure 14 shows the normalized and the enhanced image of a thyroid nodule. It is observed that the tissues are clearly visible in the enhanced image.



(a) (b) (c)

Figure 14 - Example of thyroid image preprocessing. (a) an input image; (b) cropped image; (c) enhanced image

3.2 Feature Extraction

This work uses two descriptors (HOT and PB-DCT) for thyroid nodule classification. HOT is a modification of the HOG descriptor where a Gabor filter is used to calculate the angle and magnitude response of a thyroid nodule's texture. Selected PB-DCT coefficients-based features are used here to improve the classification accuracy for each TIRADS score. Next, we discuss these two techniques separately. To the best of our knowledge, these strategies have not been applied anywhere for thyroid nodule classification based on the TIRADS score.

3.2.1 Histogram of Oriented Texture (HOT)

Here, we derive our HOT descriptor. Firstly, we discuss the calculations of gradient and orientation of an image and the HOG descriptor calculation from cells and blocks partitions(Zhu et al., 2018). Secondly, we describe a Gabor filter, which is used to extract the magnitude and orientation of tissue texture information, and finally, we discuss modifications to the HOG descriptor that involves a Gabor filter and parameter selection.

The gradient of an image I in horizontal and vertical directions, for a pixel position (x, y) is computed as:

$$\begin{aligned} dx &= I(x+1, y) - I(x-1, y) \\ dy &= I(x, y+1) - I(x, y-1) \end{aligned} \qquad \text{Eq.2}$$

for each pixel, $I(x, y)$, the gradient magnitude $m(x, y)$, and orientation $\theta(x, y)$ are computed as below.

$$\begin{aligned} m(x, y) &= \sqrt{dx^2 + dy^2} \text{ and} \\ \theta(x, y) &= \tan^{-1}\left(\frac{dy}{dx}\right) \end{aligned} \qquad \text{Eq.3}$$

Orientation range $(0^0 - 180^0)$ is quantized into B bins (i.e., $\theta(x, y) \in \text{bin } (b)$ with $b = 1,2,3, \dots, B$). The image is divided into $c \times c$ non-overlapping cells, and $l \times l$ cells are integrated as one block. Two adjacent blocks can overlap. The histogram of orientations $(HC(b)_i)$ of bin (b) within i^{th} cell is computed as

$$\begin{aligned} HC(b)_i &= HC(b)_i + m(x, y) \\ m(x, y) &\in Cell_i \\ b &= 1,2,3, \dots, B, \text{ and} \\ i &= 1,2,3, \dots, c \times c \end{aligned} \qquad \text{Eq.4}$$

The histogram of the block (HB_j) is obtained by integrating HCs (Histogram of Cells) within this block as follows:

$$HB_j = HC_1 \| HC_2 \| \dots \| HC_{l \times l}$$

where, || denotes histograms concatenation into a vector. The vector of HB_j is finally normalized by

L_2 -norm block normalization as below to obtain NHB_j.

$$NHB_j = \frac{HB_j}{\sqrt{\|HB_j\|_2^2 + e^2}}$$

where, e is a small constant to avoid the problem of division by zero. Histogram of Oriented Gradients (HOG) can be obtained by integrating normalized histograms of all blocks as below.

$$HOG = NHB_1 \| NHB_2 \| \ldots NHB_j \| \cdots, \| NHB_N$$

Where, N is the number of possible blocks in an image, which is equal to $(c - l + 1) \times (c - l + 1)$. Figure 15 shows an example of cell partitions, the formation of overlapped blocks, and histograms' concatenation to get the HOG descriptor. Finally, the length of HOG is $l^2 \times (c - l + 1)^2 \times B$.

Different line-shape filters or tools are available in the literature to extract lines and orientation features of a texture image (Simonyan & Zisserman, 2015).

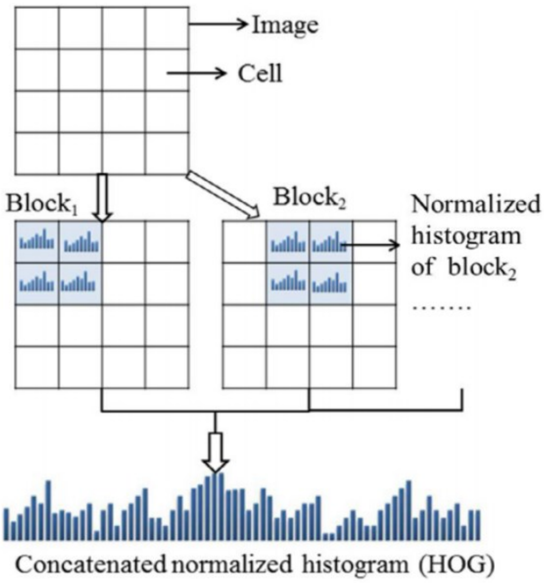


Figure 15 - HOG descriptor calculation

2-D Gabor filters have been found more suitable filter bank to extract biological-like textural features of simple cells in the mammalian visual system (Sai Sundar et al., 2019). Thus, a Gabor filter is ideal for calculating multi-orientation texture features of a thyroid nodule. A Gabor function is defined as follows:

$$G(x, y, \theta, \mu, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left\{-\frac{x^2 + y^2}{2\sigma^2}\right\} \times \exp\left[2\pi i(\mu x \cos\theta + \mu y \sin\theta)\right] \quad \text{Eq.5}$$

where $i = \sqrt{-1}, \mu$ is the frequency of the sinusoidal wave, θ controls the function's orientation, and σ is the standard deviation of the Gaussian envelop. Based upon this Gabor function, a set of Gabor filters can be created for different scales and orientations. Here, texture feature extraction for a given thyroid nodule image (I) is calculated by the real part of a Gabor filter bank with eight different orientations and a fixed scale. Gabor magnitude, $m(x, y)_{\text{Gabor}}$, and Gabor orientation, $\theta(x, y)_{\text{Gabor}}$, the response of each pixel (x, y) are computed as

$$m_{\text{Gabor}}(x, y) = \text{m} \ \left(I(x, y) * G(x, y, \theta_t, \mu, \sigma)\right) \text{ and} \\ \theta_{\text{Gabor}}(x, y) = \text{argmin}_t \ (I(x, y) * G(x, y, \theta, \mu, \sigma)) \quad \text{Eq.6}$$

where, $*$ means the convolution operation. The direction θ_t is calculated as follows:

$$\theta_{\text{t}} = \frac{\pi(t-1)}{8}, t = 1,2, \dots ,8$$

The features are calculated by varying the values of σ and μ. We combine HOG with a Gabor filter and name it as Histogram of Oriented Texture (HOT). HOT is computed in the same way as HOG, but $m_{\text{Gabor}}(x, y)$ and $\theta_{\text{Gabor}}(x, y)$ are used as magnitude and orientation of texture line instead of Eq.3.

Finally, the HOT descriptor's optimum parameters for both types of classification are chosen by experiments. The value of σ is varied from one to five to obtain an optimum number. The value of μ is computed as $\frac{1}{\sqrt{2\sigma}}$. In this work, the magnitude image is divided into equal-sized 16×16 cells. The size of a block considered is 2×2; therefore, 15×15 overlapped blocks are formed. The orientation range $(0^0 - 180^0)$ is quantized into 8 bins, and therefore, the final length of the resultant HOT descriptor is 7200. The HOT descriptor's length is considerable, and all features do not have the same discrimination capability (Song et al., 2019). Feature selection schemes help to select more appropriate features.

3.2.2 Pass Band – Discrete Cosine Transform

2D Discrete Cosine Transform (DCT) transforms images into frequency representation from the spatial form. It also provides energy compaction that helps to reduce the information redundancy by retaining only a few coefficients. DCT coefficients of $I(x, y)$ image of $M \times N$ size is calculated as follows:

$$F(u,v) = \frac{1}{\sqrt{MN}} \alpha(u)\alpha(v) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(x,y) \times \cos\left(\frac{(2x+1)u\pi}{2M}\right) \times \cos\left(\frac{(2y+1)v\pi}{2N}\right)$$
with $u = 0,1,2,\ldots,M, v = 0,1,2,\ldots,N$

Eq.7

where $\alpha(\omega)$ is defined by

$$\alpha(\omega) = \begin{cases} \frac{1}{\sqrt{2}} & \omega = 0 \\ 1 & \text{otherwise} \end{cases}$$

DCT based various feature extraction and compression techniques have been proposed in the literature (Sudarshan et al., 2016). Usually, DCT features are formed by selecting the most prominent and discriminating coefficients based upon some criterion (Sudarshan et al., 2016). The DCT coefficients can be divided into three sets, low frequencies, middle frequencies, and high frequencies. Low frequencies are correlated with illumination conditions; middle frequencies represent texture features, while high frequencies represent small variance or noise. Illumination and texture properties are essential for thyroid nodule classification. Therefore, this work uses low and middle coefficients to form the descriptor (the Pass Band - Discrete Cosine descriptor or abbreviated as PB-DCT). Finally, the more discriminate DCT coefficients are selected based upon a discrimination criterion, discussed in the next section.

3.3 Feature Selection

All features do not have the same ability to discriminate various classes (benign-malignant and TIRADS scores) (Song et al., 2019), and they do not increase the accuracy based on available information for each class. Therefore, it is necessary to eliminate irrelevant features and select the most discriminative features among a given set of features. There exist many techniques for feature selection. Some of the common ones are as follows: PCA (Principal Component Analysis) method, Markov blanket method, wrapper methods (e.g., sequential selection algorithm, etc.), filter methods (e.g., Pearson correlation criteria, mutual information, etc.), embedded methods, and statistical measures-based methods (e.g., *T*-test, Kolmogorov–Smirnov test, etc.) (Ouyang et al., 2019).

Out of these, wrapper methods, filter methods, and statistical measures-based methods are usually used for thyroid nodule classification. Wrapper methods are computationally expensive since the number of steps required for obtaining the feature subset is very high. Filter methods sometimes lead to a redundant feature subset, and hence, are not optimal in this sense (Ouyang et al., 2019). Thus, we go for statistical measures-based methods since they do not have the drawbacks mentioned above. These methods also have the advantage of reducing the feature space without significantly degrading the classification performance. The T-test method is one such method that gives a high score to features that capture the texture and the shape of thyroid nodules. As earlier, capturing texture is very important to us. Moreover, the *T*-test method is computationally light, and easy to implement. Thus, we use this feature selection method and show in the results section that this works very well with the two descriptors (DP-HOT and DP-PB-DCT). We term it as Discrimination Potentiality (DP) because of its capability in discriminating between the available features.

The discrimination potentiality DP_k of the k^{th} feature between two classes (a and b) is computed from a given training set as follows:

$$DP_k = \frac{\mu_{a,k} - \mu_{b,k}}{\sqrt{\frac{\delta_{ak}^2}{n_a} - \frac{\delta_{b,k}^2}{n_b}}} \qquad \text{Eq.8}$$

where $\mu_{a,k}, \mu_{bk}$, and $\delta_{ak}, \delta_{b,k}$, are mean and standard deviation values of the k^{th} feature for a and b classes, respectively. n_a and n_b are the number of thyroid nodules for a and b classes, respectively. A high value of DP means high discrimination ability of the corresponding feature.

All features (columns) of the feature matrix are arranged in descending order of their *DP* value. Initially, the first 100 features with the highest *DP* values are chosen for classification accuracy. Then, classification accuracy is calculated by adding features, with the next higher value of *DP*, one by one until we get the highest accuracy. The optimum subset of features corresponding to the highest accuracy is selected as the final descriptor.

3.4 Minority Oversampling

If the instances for one class are relatively less than the instances for other class, then the dataset comes under an imbalanced dataset category. In this scenario, we have two classes: the majority class and the minority class. Thus, in this context, many classification algorithms have low accuracy for the minority class. The most common way to solve this problem is to use Synthetic Minority Over-sampling Technique (SMOTE) (Raghavendra et al., 2017). This technique resamples the original dataset, either by under-sampling the majority class and/or oversampling the minority class. Here, we perform the oversampling of the minority class, so that number of instances for both the classes are almost similar.

In stage 1, the minority class is 'Benign', and in stage 2, the minority class among the benign cases is of TIRADS 2, and the minority class among the malignant cases is of TIRADS 5.

Chapter 4

Experimental Results

4.1 Dataset and Experimental Setup

As mentioned earlier, we use the TDID database for our experiments, which consists of 349 images. Each original image is of size 360 × 560, which becomes 300 × 300 after pre-processing. Out of these, 61 are benign, while 288 are malignant. Table 5 lists the number of images in TDID based on the TIRADS classification.

TIRADS	No. of Images	Classification (Total Images)
2	42	Benign (61)
3	19	
4	243	Malignant (288)
5	45	

Table 5 - Distribution of benign and malignant images according to TIRADS

Experiments are carried out in MATLAB[R]2021 on a machine with HP ProBook an Intel i5 processor @2.5 GHz and 4GB RAM. Our system's performance (and comparative systems) is evaluated by standard metric of sensitivity, specificity, and accuracy.

We first use two-fold cross-validation, where the dataset is randomly divided into two equal parts. One part is used for training, and the other is used for testing. Then, the two parts are swapped, i.e., the one used for training earlier is now used for testing, and the one used for testing earlier is now used for training. At the end of this exercise, average performance is saved. Finally, we repeat two-fold cross-validation ten times to remove any bias related to the dataset's division.

4.2 Criteria for Classification Performance

To measure a thyroid classification system's performance, three popular metrics have been in use, including sensitivity, specificity, and overall classification accuracy. Like the previous studies, we also used these three performance measurements in our experiments to measure our proposed method's performance.

Sensitivity is computed as the number of true positive cases over the number of actual positive cases. It is represented as follows:

$$Sensitivity = \frac{TP}{TP + FN} (\%) \qquad \text{Eq.9}$$

where, TP means True Positive cases and FN means False Negative cases.

Specificity is computed as the number of true negative cases over the number of actual negative cases. It is represented as follows:

$$Specificity = \frac{TN}{FP + TN} (\%) \qquad \text{Eq.10}$$

where, TN means True Negative cases and FP means False Positive cases.

Accuracy is computed as the number of correct classifications over the number of given cases. It is represented as follows:

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} (\%) \qquad \text{Eq.11}$$

4.3 Result and Comparison of stage 1

Since CAD for a thyroid nodule classification system typically focuses on two different aspects of the classification problem: the correct classification of benign case images and correct classification of malign case images, the specificity, and sensitivity measurements were used to measure the accuracy of these aspects. First, the sensitivity was measured as the ratio between the true positive (TP) samples (samples that are malignant case images are correctly classified as the malignant ones) over the total number of the image of the malignant case (TP + false negative (FN)) in a test dataset as shown in Eq.9. Second, the specificity is the measurement of true negative (TN) samples (samples that are benign cases are correctly classified as benign ones) over the total number of benign case images (TN + false positive (FP)) in a test dataset, as shown in Eq.10.

To access an overall (average) ability of the classification system, the third measurement (overall accuracy) was used and measured by the total number of correct classification/detection samples (true positive and true negative samples) over the total number of samples in a test dataset as shown in Eq.11.

Sr. No.	**Descriptors**	**Sensitivity**	**Specificity**	**Accuracy**
1	Image Augmentation(Dabbaghchian et al., 2010)	94%	93%	94%
2	VGG-16 (Chawla et al., 2002)	100%	88%	94%
3	Google Net (Chawla et al., 2002)	-	-	79%
4	Circular Mask (Raghavendra et al., 2017)	95%	64%	91%
5	CNN (Raghavendra et al., 2017)	96%	66%	92%
6	DP-HOT	100%	90%	96%
7	DP-PB-DCT	90%	70%	90%

Table 6 - Comparison of classification accuracies for various descriptors on the TDID dataset with our descriptor DP-HOT (6)

We compare the performances of the descriptors with the five existing ones mentioned earlier for benign and malignant classification. The results for this are given in Table 6. From this table, it is evident that DP-HOT (6) performs better than DP-PB-DCT (7) which been used in this study cause it has the higher accuracy rate in the use of (TDID) dataset than all other dicriptors.

4.4 Results of Stage 2

The second stage of the thyroid nodule classification system operates on two parts, i.e., benign and malignant. Each part focuses on the binary classification between TIRADS, i.e., correct classification of TIRADS 2 and TIRADS 3 images in the benign part, and TIRADS 4 and TIRADS 5 images in the malignant part. For this purpose, specificity and sensitivity measurements were used to measure the accuracy of these aspects.

First, the sensitivity is measured for TIRADS 2 in the benign part and TIRADS 4 in the malignant part, as shown in Eq.9. Second, the specificity is measured for TIRADS 3 in the benign part and TIRADS 5 in the malignant part, as shown in Eq.10. The sensitivity reflects the ability of a classification system to correctly detect TIRADS 2 cases and TIRADS 4 cases. In comparison, the specificity reflects the ability of a classification system to correctly detect TIRADS 3 cases and TIRADS 5 cases. To access the overall (average) ability of the classification system, overall accuracy was used as shown in Equation (9).

The results for the 2nd stage are given in Table 7. From this table, it is evident that DP-HOT performs better than DP-PB-DCT.

	Descriptor	**Sensitivity**	**Specificity**	**Accuracy**
Benign	HOT	100%	90%	96%
	PB-DCT	90%	80%	90%
Malignant	HOT	89%	88%	91%
	PB-DCT	90%	80%	90%

Table 7 - Results of the second stage

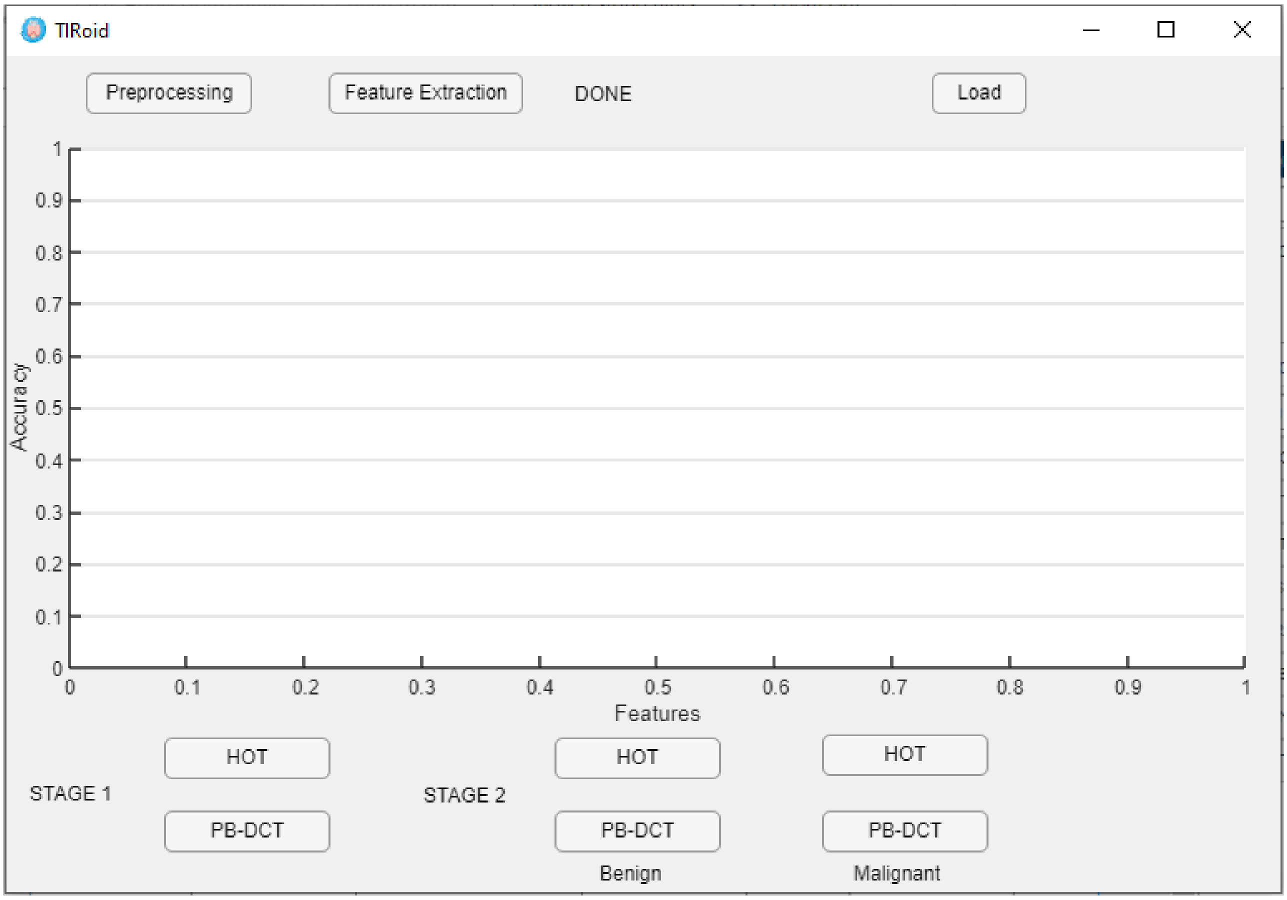


Figure 16 main picture of the programm used TIRoid

Benign

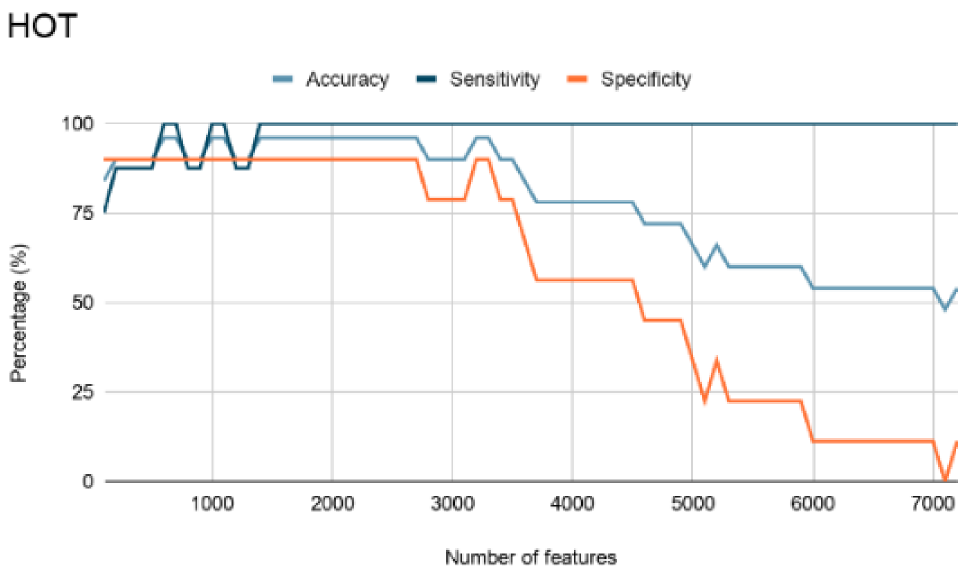


Figure 17 - Performance of Benign-HOT

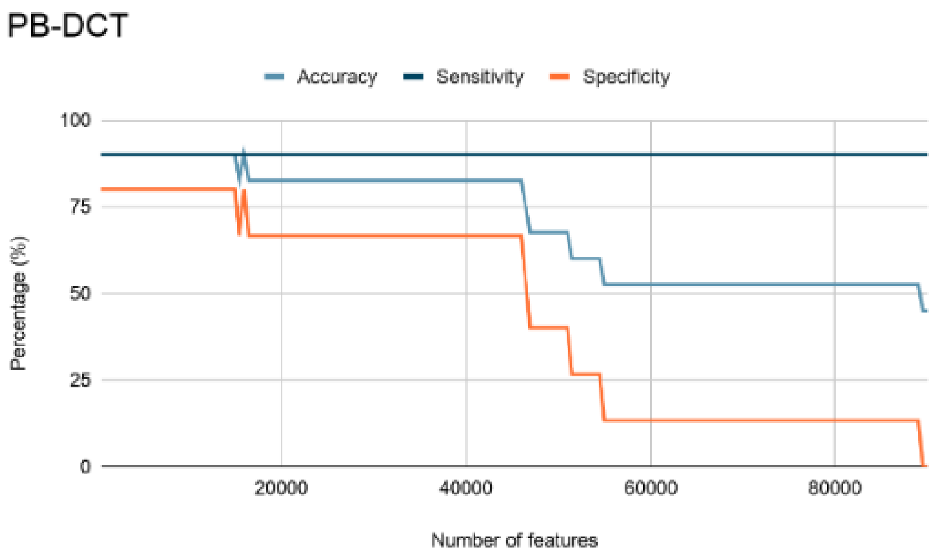


Figure 18 - Performance of Benign-PB-DCT

Malignant

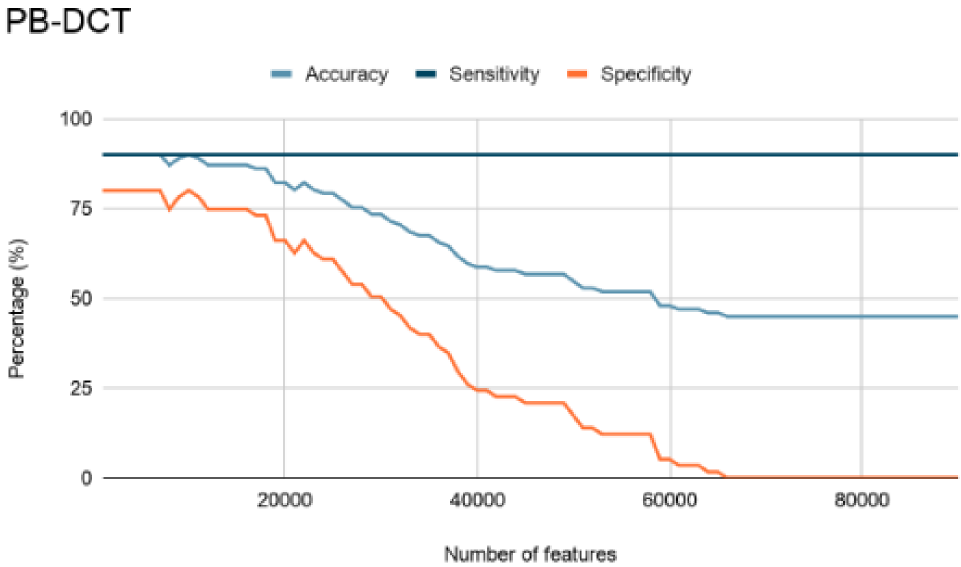


Figure 19 - Performance of Malignant-PB-DCT

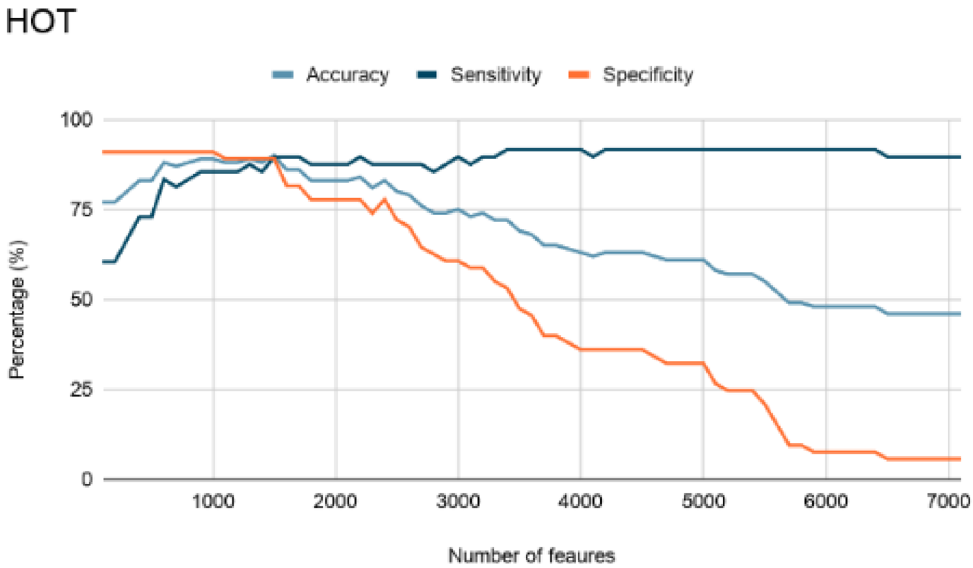


Figure 20 - Performance of Malignant-HOT

Conclusion and future work

We present the two-stage thyroid nodule classification method using texture exploiting descriptors (HOT and PB-DCT). In the first stage, the thyroid nodules are classified as benign and malignant. The benign and malignant nodules are further classified based on their TIRADS classes. In the second stage, benign nodules are further classified as nodules with TIRADS scores 2 and 3, and malignant nodules are classified as nodules with TIRADS scores of 4 and 5. This two-stage classification has not been done in any of the previous works. We achieve 96% accuracy for benign classification and 91% accuracy for malignant classification.

In the future, we plan to use the XML metadata associated with each thyroid nodule image to obtain more sensitive regions. It contains the coordinates of the region where the tumour might be present. Extracting features from this region may give more accurate features to classify the images. This can further improve the classification accuracy of our method.

Also the rise of deep learning and AI has the potential to improve and reform future medical diagnosis system. This thesis has only explored a tiny corner of a much bigger picture. Even in the field of thyroid tumor diagnosis, there are many promising future directions that are worth exploring.

First, future studies can try to predict some expert-determined features. If a machine can characterize a thyroid tumor image on a professional level, it can greatly lower the cost of medical data acquisition process. Moreover, having such system can help automate the thyroid nodule diagnosis workflow, which can significantly save labor costs and make high quality medical diagnosis more affordable.

Second, one can also study the importance of different features and transform them into medical knowledge and improve current thyroid diagnosis system. Studying the importance of different features can also help us eliminate irrelevant information in the input and build better performing models.

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