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Review

Expert Systems for Farmed Fish Disease Diagnosis: An Overview and a Proposal

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Abstract: The expert system approach, although quite old, is still quite effective in scientific areas where experts are required to make diagnoses and predictions. One of those areas is fish disease diagnosis. It is an application domain that currently employs complicated processes, which require high level skills for making accurate diagnoses. On the other hand, complete datasets for full diagnosis to be able to use machine learning techniques are not available. Therefore, in aquaculture, now more than ever, fish farmers do not have the required expertise or equipment to accurately diagnose a fish disease. For that reason, expert systems that can help in the diagnosis, prevention, and treatment of diseases have been developed. In this paper, we attempt to give an overview of the expert system approaches for fish disease diagnosis developed in the last two decades. Based on the analysis of their technical and non-technical characteristics, we propose an expert system architecture and a fish disease diagnosis process aiming at improving the deficiencies of the existing systems. The proposed system can handle all types of fish diseases based on image and non-image data as well as on molecular test results and can provide explanations. The diagnosis process goes through four consecutive levels, where each next level considers an additional category of parameters and provides diagnoses with a higher certainty.

Keywords: expert systems; aquaculture; fish health management; fish disease diagnosis

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1. Introduction

With the rapid development of aquaculture worldwide, the need for quality seafood products has become almost imperative [1]. Fish is an important source of protein required for the human body, and it is suggested as a "healthy diet" to consumers [2]. Therefore, the consumption of fish products is continuously increasing together with the demand for its "sustainable" supply [3]. The same issue happens with the development of marine fish farming [4]. The management of fish farming concerns various tasks, such as species identification, fish counting, fish health and welfare management including disease diagnosis and treatment, fish product marketing, etc. [5,6]. Contemporary management requires the automation of those tasks alongside precision [7,8].

The most important and challenging task is fish disease diagnosis and treatment. Quite often, the appearance of diseases in the fish farms restricts the quality and the overall fish production [9]. Fish disease is considered a major factor causing about 50% of overall production loss [10], generating severe insurance claims for compensation [11]. On the other hand, most farmers have trouble identifying and treating fish diseases, because they lack the necessary expertise and experience to do so [12]. Therefore, it is necessary to develop systems that can automatically predict and/or diagnose fish diseases in real-time, to keep fish healthy and safe, and to prevent and control disease transmission in aquaculture. To achieve that, artificial intelligence (AI) techniques should be employed [13].

The diagnosis of fish diseases is a classification problem. There are two general AI approaches to tackle such a problem: the expert system (ES) approach and the machine learning (ML) approach [14,15]. An expert system is a computer program that reasons in a similar way to a human expert. It mainly includes a knowledge base, which often consists of if-then rules, and an inference engine, which uses the rules to produce conclusions. To construct an expert system, you need to acquire knowledge from experts and represent it in the knowledge base. A machine learning approach consists of finding a model, called a classifier, that can detect fish diseases. Such a model can be a decision tree, a neural network (NN), or a statistical model. To be able to construct such a model, you need to have an adequate dataset consisting of real cases. Modern deep neural networks (DNNs) require very large datasets to be trained.

The full diagnosis of fish disease considers a variety of parameters: environmental, clinical, microscopic, and molecular [16]. Although the expert system approach is quite old, it still dominates as an approach for full disease diagnosis. This is because good, real datasets including all parameters are not available. Therefore, modern ML approaches, such as deep learning (DL), are used only for image-based diagnosis, which, however, is part of a full diagnosis. Image-based diagnosis alone cannot give definite disease results, but only detect problematic situations [13]. Image-based diagnosis with "traditional" ML algorithms, such as Naïve Bayes, k-NN, SVM, and Random Forest, are used for image-based diagnosis, after image preprocessing, which results in feature extraction; hence, in the creation of a dataset. DL networks, such as Convolutional Neural Network (CNN), do not require image preprocessing, but require a very large number of images to be trained, which are usually not available. On the other hand, ML methods act in the same way as black-boxes and cannot explain their reasoning, which is very important in such cases [17].

To the best of our knowledge, none of the existing fish disease diagnostic systems considers all the above parameters for their diagnosis. So, their diagnosis is rather approximate. In this paper, we focus on the expert system approach for fish disease diagnosis, which is the basis for a complete diagnosis. Therefore, we present an overview of such systems created during the last two decades and specify their characteristics, such as the AI approach they use and the types of fish and diseases they cover. Based on this, we propose an intelligent system for full fish-disease diagnosis, which combines a traditional ES approach with pattern matching or a ML approach for image-based diagnoses.

The organization of the paper is as follows: Section 2 presents the collection of the works that utilize expert systems for fish disease diagnosis, Section 3 constitutes a small description of the development of our own expert system and Section 4 concludes the paper.

2. Background Knowledge

2.1. Knowledge Representation in Expert Systems

An expert system consists of three main units, the knowledge base (KB), the inference engine (IE), and the database (DB) (Figure 1). The KB contains the expert knowledge, represented via a knowledge representation (KR) language, as expressions of the KR language. The IE uses the expressions in the KB to make inferences, i.e., to produce new facts. The DB is a storage space, where initial facts about a problem and produced (new) facts by the IE are stored. There are several KR languages used in expert systems [18,19]. The most common in expert systems for fish disease diagnosis are presented in this section.

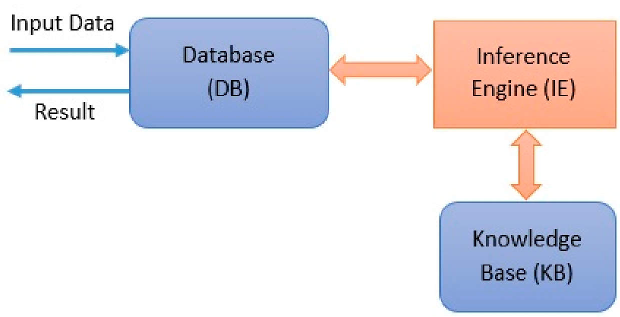

Figure 1. Basic expert system architecture.

2.1.1. Production Rules

Production rules is the oldest and most popular KR language used in expert systems and the one that characterizes them. Their popularity comes from the fact that they are natural representations of human knowledge, which makes it easy to comprehend the represented knowledge. Fish disease domain is one of those where rule-based expert systems are used for diagnoses. In such cases, each rule represents a piece of knowledge that reflects the way an expert (ichthyologist) makes diagnoses: from various evidence (e.g., clinical symptoms, fish images, and test results) they make a hypothesis (diagnosis) about the disease of a fish. The basic structure of a rule is the following:

if <antecedents>
then <consequence>
where <antecedents> represent evidence and <consequence> the hypothesis. The antecedents of a rule are connected between each other with logical connectives, commonly with "and". When the antecedents of a rule hold (or observed), the consequence is derived, and the rule is said to be fired. Rules represent general knowledge regarding a domain. The following is an example rule:
R1: **if** fish-body is pale **and** fish-belly is swollen **and** fish-excrement is no
then fish-disease is dropsy

In such systems, there are two basic inference strategies: forward chaining and backward chaining. The first, also called bottom-up, is more common and natural for such cases; it starts from the evidence (known facts in the DB) and goes towards the hypotheses, to find the disease(s). Technically, IE finds the rules that can fire and produce their conclusions, until a fish disease conclusion is reached. The second, also called top-down, starts from the hypotheses (conclusions) and tries to reach the evidence (known facts). Technically, IE finds rules that have a conclusion related to a disease and examines whether their evidence (antecedents) holds.

The forward chaining process in a rule-based system is as follows:

1. Initialize the database (DB);
2. Repeat
    2.1. Find the fireable rules (conflict set)
    2.2. If there is no fireable rule, stop (failure)
    2.3. Select one of the fireable rules
    2.4. Update DB with the conclusion of the rule

    Until DB contains a solution fact;
3. Stop (success).

2.1.2. Rules with Certainty Factors

Given that in many situations, things are not always certain, there is a need to represent that uncertainty in the KB. Certainty may refer to a rule itself or to the evidence. Rules provided by experts may be not 100% certain. Certainty Factors (CFs), introduced in the expert system MYCIN [20], is an old, empirical, but widely used method of dealing with uncertainty in rule-based systems, especially in the medical domain [21].

CFs can take values in the interval $[-1, 1]$, where "-1" means "totally uncertain", "1" means "totally certain", and "0" means "undefined" (this is an impractical case). Usually, CFs take positive values. The above rule is presented below, using rule CF:

R1: **if** fish-body is pale **and** fish-belly is swollen **and** fish-excrement is no
then fish-disease is dropsy (0.8)
where $CF_{R1} = 0.8$. This means that the rule has certainty 0.8, that is when it is fired and fact "fish-disease is dropsy" is derived, it has a certainty CF = 0.8 (out of 1.0). When using CFs, more than one rule having the same consequent (hypothesis), but different antecedents, may be fired. In such a case, if we have two rules, R1 and R2 with certainties CF_{R1} and CF_{R2}, the common consequent is derived with a certainty CF_{R1R2} calculated by the following

formula (which can be used for more rules consecutively), given that CF_{R1} and CF_{R2} are positive:

$$CF_{R1R2} = CF_{R1} + CF_{R2}\,(1 - CF_{R1})$$

In the case when the truth of the antecedents (evidence) is not totally certain, the certainty of the consequent is also reduced. For example, in the above rule, if we have the following CFs for the three antecedents, CF1 = 0.6, CF2 = 0.8, and CF3 = 1.0, the CF of the consequent will be calculated as follows:

$$CF = CF_e * CF_{R1},\ CF_e = \min\,(CF1, CF2, CF3)$$

given that we have only the "and" connective in the antecedents. So, CF = min (0.6, 0.8, 1.0) ∗ 0.8 = 0.6 ∗ 0.8 = 0.48.

Although CFs can be theoretically calculated via two measures, the measure of belief MB and the measure of disbelief MD, in practice, due to the difficulties in calculating the required probabilities, a rule's CF is provided by the expert(s) during the design of RB, and the CFs of the antecedents are provided by the user(s) of the system, when asked to input values. Alongside a value, they are asked about how certain the value is. In such systems, all possible results are derived and the one with the largest CF is proposed as the answer.

2.1.3. Fuzzy Logic and Rules

Another way to represent uncertain knowledge is using aspects of fuzzy logic [22] in rules. Fuzzy rules are the same as normal production rules, where, apart from the fact that only linguistic values are allowed for the variables in the antecedents, the values are represented as fuzzy sets. A fuzzy set is a set for which the relation "belongs to" has not only two values, yes (1) and no (0), but all the values in [0, 1], where "0" means does not belong and "1" means (fully) belongs. So, an element may belong to a (fuzzy) set in a degree of 0.8 (out of 1.0), which is called the membership value or degree of membership denoted by μ. Fuzzy sets are used to represent vague expert expressions, such as "very much", "slight", "little", "medium", etc., in cases where we have variables with numerical values. For example, in Figure 2 the fuzzy variable 'body-wounds' has three fuzzy (linguistic) values: 'minor', 'medium', and 'major', which are represented as fuzzy sets (having a trapezoid scheme). The horizontal axis represents the values of "body-wounds" and the vertical axis represents the membership value. So, if wounds cover 37% of the fish body, this value denotes that wounds are by 0.8 'medium' and by 0.4 'major'.

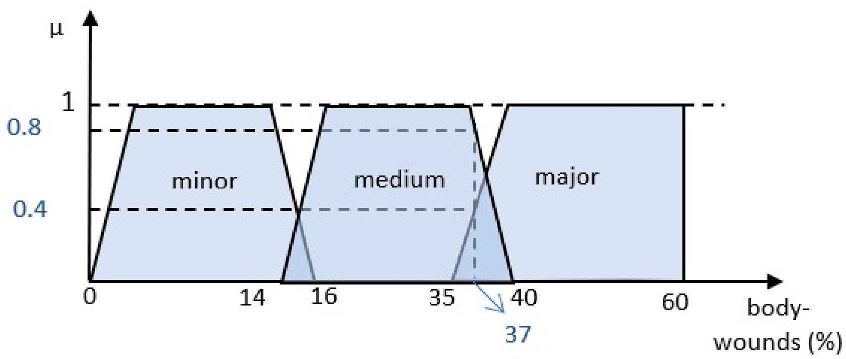

Figure 2. Fuzzy sets as linguistic values.

Below is an example of a fuzzy rule, where S1, S2, and S3 are symptoms, D1 is a disease, and 'slight', 'little', 'severe', and 'medium-certain' are linguistic (fuzzy) values.

R2: **if** S1 is slight **and** S2 is little **and** S3 is severe
then D1 is medium-certain

Given that the input values of fuzzy variables are numerical, it is necessary to convert them into fuzzy ones, to be able to work with the rules. This is called the fuzzification process. If the antecedents of a fuzzy rule match the facts in DB, the rule is fired. Now, the firing of a rule is a different process than in normal rules. Some inference rule is applied to the membership values of the linguistic values of the antecedents of the rule, its result is applied to the consequent, and a fuzzy set of the variable of the consequent is produced. Again, all rules that can be fired are fired and their results (fuzzy sets) are combined to produce the final result, which consequently needs to be converted into a numerical value to be comprehensive. For example, the shape in Figure 3 is a potential result for D1. To convert it into a crisp value, various methods can be used. The most common of them is the 'centroid method', which finds the ordinate of the gravity center of the shape (for example, 62.5 in our case). This is called the defuzzification process.

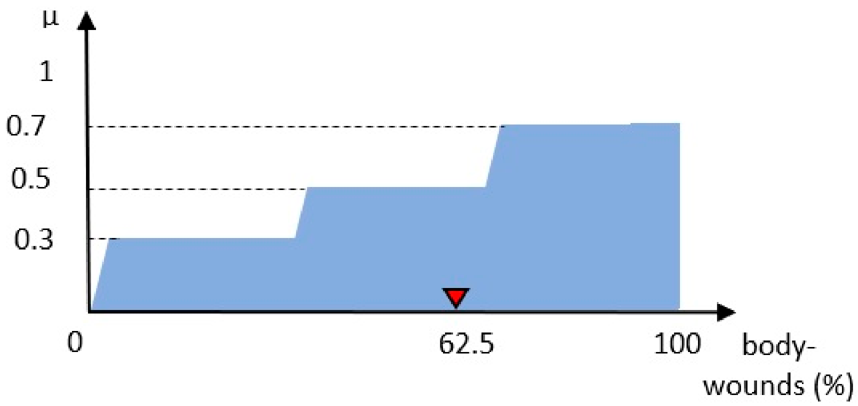

Figure 3. Defuzzification example.

Because of the above, the architecture of a fuzzy expert system is different from that of a normal one. It is depicted in Figure 4, where the Fuzzy Inference Engine (FIE) is the fuzzy reasoning mechanism. When a final result is produced, it goes through the Defuzzification unit. Again, here, more than one rule can be fired and produce different results. The one with the most certain value is proposed as final. The difficulty in this approach is the specification of the fuzzy sets, apart from the knowledge acquisition from the expert(s).

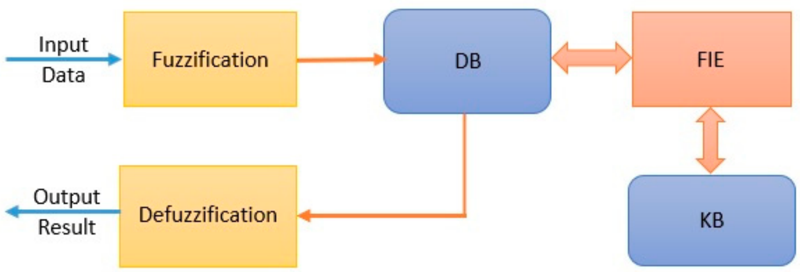

Figure 4. Basic Fuzzy Expert System Architecture.

2.1.4. Case-Based Representation

Case-based reasoning (CBR) is a relatively recent knowledge representation and reasoning method. The main idea is to store a large set of previous (solved) cases with their solutions in a case base (or case library) and use them to deal with (solve) new (similar) cases [23,24]. There is no specific method for the representation of stored cases. Various KR schemes can be used for that, such as semantic nets, frames, objects, patterns, even rules; the frame or object-based representations dominate. So, CBR is a reasoning method rather than a representation one.

CBR works in a way that can be represented by the so-called CBR cycle [25]:

1. retrieve the most similar case(s);
2. reuse those case(s) to create a solution;

3. revise the solution to adapt to the case(s);
4. retain the produced case as a new case.

Whenever, a new input case has to be dealt with, the case-based system performs an inference following those four phases. In the retrieval phase, the system retrieves from the case base the most relevant stored case(s) to the new case. In the reuse phase, a solution for the new case is created based on the most relevant case(s) that are retrieved. The revise phase validates the correctness of the proposed solution, perhaps with the intervention of the user. Finally, the retain phase decides whether the knowledge learned from the solution of the new case is important enough to be incorporated into the system's case base.

Indexing is a mechanism necessary for assigning indices to stored cases to assure their efficient retrieval. Several indexing methods have been used, such as checklist-based indexing, difference-based indexing, inductive learning methods, and explanation-based techniques. Similarity assessing methods are also necessary for best matching case(s) retrieval. Similarity metrics assess the relevance of the retrieved cases to the new case. There are various methods, such as the nearest neighbors approach, the most used for small case bases, and induction-based methods.

Quite often the solution contained in the retrieved case(s) is adapted to meet the requirements of the new case. The usual adaptation methods are substitution, transformation, and derivational replay. For the adaptation task, domain knowledge, usually in the form of rules, is employed. Incorporation of knowledge during the operation of a case-based system enhances its reasoning capabilities. Case-based representation and reasoning has its own advantages and disadvantages compared to rule-based representation and reasoning [26].

2.2. Neural Networks

Apart from the expert system approach, the machine learning approach (ML) is also used in classification problems [27]. The ML approach more often used for fish disease diagnosis is artificial neural networks (ANNs). An artificial neural network (or simply neural net) is a parallel and distributed structure. A neural net consists of several interconnected nodes, called neurons. There are weights attached to the connections between neurons: each connection from a neuron u_j to a neuron u_i is associated with a numerical weight $w_{i,j}$, which represents the influence of u_j to u_i. Each neuron also has a weight attached to itself, called the bias. Each neuron acts as a local processor, which computes its output (connection) (u_i) based on the weighted sum of (the values of) its input connections (u_1, u_2, . . . , u_n) and an activation function f (see Figure 5). The activation function may be of various types: a threshold, a sigmoid function, the softmax, the relu, etc. The connection weights and the structure of a neural net define its behavior [28].

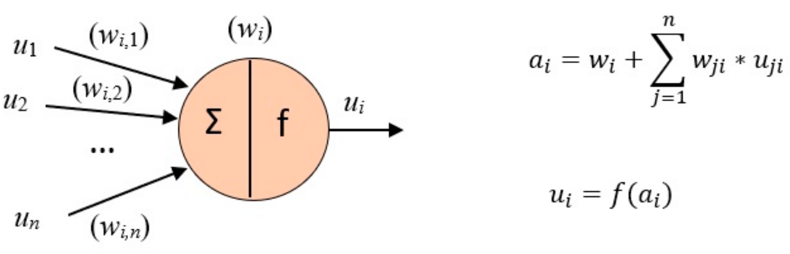

Figure 5. Computational Model of Neuron.

The most popular neural net architecture is the feedforward network. Feedforward neural networks (FNNs) are nets that do not contain cycles. They are usually organized in layers. So, we distinguish between the input layer, intermediate layer(s), and output layer (see Figure 6). The input layer consists of input neurons (illustrated as rectangles in Figure 6), which are pseudo-neurons used to transfer externally provided values to neurons to further layer(s), do not perform any computation, and are taken as the inputs of the network. The outputs of the neurons at the output layer are taken as the outputs of the network. Intermediate neurons are used for intermediate computations and are often called hidden neurons.

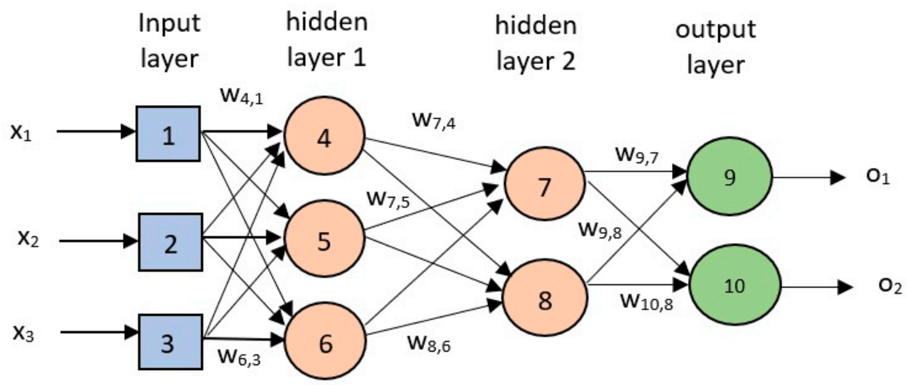

Figure 6. A two-layer feedforward neural network.

A neural net can store empirical knowledge and make some kind of inference. Empirical knowledge comes in the form of training examples. Each example consists of input values and the corresponding correct output. They are used to 'train' the net, i.e., to calculate the weights so that the training examples are correctly classified (i.e., the combination of the inputs in each example produces the specified output). This is called the supervised learning model (the other is called the unsupervised learning model, where no correct outputs are specified). There are several training algorithms for supervised learning. A well-known training (or learning) algorithm is back-propagation [29]. Thus, neural nets are representatives of empirical machine-learning systems. Empirical learning usually requires a large, but possibly incomplete, training set from which they can generalize. They may also need some domain knowledge such as information regarding the most relevant features of the training examples as well as the values they can take. Knowledge can be represented in a neural net via its topology and its weights if some semantics are attached to neurons and the activation values. For example, semantics may include associations between concepts of the problem and neurons of the network.

Neural networks of more than two hidden layers and large number of neurons are called deep neural networks (DNNs). There have been many types of DNNs, depending on their architecture and the domain they apply. For example, CNN is a type of DNN that is very effective in image-based recognition, and consists of many different types of layers, such as convolutional layer, max pooling layer, etc. [30]. In addition, more effective learning algorithms, such as Adam [31], are used in such cases. Neural networks have their own advantages and disadvantages compared to rule-based representation and reasoning.

2.3. Fish Diseases and Diagnostic Parameters

Fish diseases can be distinguished in the following categories [32]:

- Parasitic;
- Bacterial;
- Viral;
- Fungal.

Parasitic infections are caused by various parasites, including protozoans, metazoans, monogeneans, and cestodes. Symptoms can include skin and gill irritation, weight loss, and poor growth. Bacterial infections are caused by various bacteria, including Aeromonas, Pseudomonas, Vibrio, and Edwardsiella. Symptoms can include ulcers, fin and tail rot, and swollen eyes. Viral infections are caused by viruses such as Infectious Hematopoietic Necrosis Virus (IHNV), Viral Hemorrhagic Septicemia Virus (VHSV), and Infectious Pancreatic Necrosis Virus (IPNV). Symptoms can include lethargy, abnormal swimming behavior, and hemorrhaging. Finally, fungal infections are caused by various fungi, including Saprolegnia and Achlya. Symptoms can include white or gray patches on the skin or fins.

Diagnosis of fish diseases is based on several diagnostic parameters [33] that could be categorized as follows:

- Environmental parameters;
- External clinical signs
    - Physical signs
    - Behavioral signs;
- Internal clinical signs;
- Microscopic image findings;
- Molecular test results.

Environmental conditions refer to parameters such as water temperature, water quality, and the growth phase of the fish, which is mainly related to the weight of the fish. External or visual clinical signs concern situations that are observable by eye. We can distinguish them in physical and behavioral ways. Physical symptoms of fish disease can include changes in skin color, ulcers or lesions on the skin, fin rot or other damage to the fins, and abnormal growths or swellings. Behavioral symptoms refer to changes, such as decreased activity, loss of appetite, hiding or remaining in one area of the tank, and abnormal swimming patterns. Internal signs are more difficult to diagnose, and may include changes in the size, shape, or color of internal organs, or the presence of abnormal fluids or growths within the fish's body. Dissection of the fish is required to trace such signs. Microscopic examination of fish tissues or fluids can provide important diagnostic information in the identification of fish diseases. When examining tissues or fluids under a microscope, veterinary professionals or fish health experts can look for signs of infection or inflammation, such as the presence of bacteria, fungi, parasites, or abnormal cells. Molecular diagnostic tests can help to identify the specific pathogens causing fish disease by analyzing DNA or RNA sequences. These tests can be very accurate and can help to guide treatment decisions. So, a complete diagnosis of a fish disease may require taking into account all the above parameters.

Systems can also use two types of data for specifying values of parameters:

- Image data;
- Non-image data.

Image data are mainly used to obtain values for external behavioral and internal clinical signs.

3. Expert Systems for Farmed Fish Disease Diagnosis

A variety of expert systems have been developed since the last century, to help fish farmers deal with fish diseases. Those systems are often able to achieve disease diagnosis and treatment in time, as well as provide consultancy for the prevention of further fish infection. Most of them use traditional expert-system approach methods. In this section, a collection of works utilizing expert systems for fish disease diagnosis and treatment in the last 20 years is presented. We present them in groups of ESs that use the same or similar AI approaches.

3.1. Pure Rule-Based Systems

Fish-Expert [34] is a web-based expert system for fish disease diagnosis which can diagnose about 126 kinds of fish diseases related to 9 primary freshwater fish. It consists of the traditional modules of expert systems, such as a knowledge base and an inference engine, as well as a database (where material about symptoms, diseases, microscopic examinations, etc., is stored), a knowledge elicitation tool, an explanation module, and a fish-farming information system. The online fish-farming information system provides information about fish farming and is being constantly updated. The knowledge base contains the rules which are matched with the symptoms to identify the disease and treatment and the inference process is responsible for querying the system. Knowledge was acquired by using questionnaires (sent to 130 fish farmers) and by interviewing 35 fish disease experts. Rules diagnose diseases and propose treatments. Finally, a multimedia interface allows the users to choose text and images to describe fish symptoms.

In [35], the authors created an expert system for the diagnosis of diseases of the freshwater Betta fish (Betta splendens). They use a forward chaining rule-based approach, where rules were produced from a disease–symptoms association table completed by experts in the field and related sources of knowledge, which afterwards was converted in a decision tree. Only external clinical signs are considered. The system interface includes a cultivator menu, where the cultivator reports the fish problem for which consultation by the system is needed, and a disease menu, where information about Betta fish diseases is displayed as well as the cases of users who visited the system. No evaluation of the system is reported.

The system in [36] uses a forward chaining rule-based approach for Catfish (Silurus glanis) disease diagnosis. Again, a disease–symptoms association table is used for extracting production rules. The system provides an interface for problem data input and a result display after diagnosis is performed. Only external clinical signs are considered. No evaluation of the system is reported.

3.2. Systems Using CFs

The Fish Intelligent Decision Support System (FIDSS) is dealt with in [37], where the phases of its development are presented in detail. The final representation scheme is rules with CFs in their antecedents, where CFs are calculated as the posterior diagnostic probabilities. Each CF denotes the significance of the corresponding antecedent in drawing the conclusion (consequent) of the rule. Additionally, each rule is assigned a CF. Probabilities were calculated based on 300 fish clinical records. A hybrid reasoning mechanism combining forward and backward reasoning was adapted at the intermediate stage of the system development. A set of suspicious diseases was specified through forward chaining and a set of suspicious symptoms through backward chaining. A decision was made after comparing and matching the inputted symptoms with the suspicious ones. Finally, parsimonious covering theory was adapted as the core reasoning mechanism.

The Expert System of Catfish Disease Determinant [38] is another example of an expert system based on the CFs method. It does not use rules but works directly with CFs. Symptoms are associated with diseases of Catfish (Silurus glanis) and a weight is associated with each symptom, representing its influence on the associated diseases. Sixteen symptoms and seven diseases are considered in total. The user is asked to specify the symptoms and the system calculates the CFs of all affected diseases. The disease with the larger CF is the most certain. The MYCIN expert system's calculation formulas are used. Three example cases are provided. However, there are a few problems with this paper. First, the provided CFs (weights) have only two different values (0.7, 0.8). Second, the same weight of each symptom is considered for all diseases, which may be not reasonable. Third, there are incorrect calculations in the paper.

In the Expert System of Diagnosing Koi's Fish Disease [39], rules with CFs are used for knowledge representation and reasoning. A Koi fish (Cyprinus Carpio haematopterus) disease–symptoms association table is used for extracting rules. The weights of the symptoms were specified by numerical interpretation of the uncertain terms (e.g., not probably, maybe not, probably, almost certainly) used by the experts during knowledge elicitation and considered as CFs of corresponding rule antecedents. In addition, rule CFs were assigned in the same way. Only external signs are considered. An interface with five menus was constructed. The most important are: information menu (refers to diseases and symptoms), input menu (for providing current case data), and diagnosis menu (displays diagnosis result). The users can complete an input form by choosing the symptoms of the koi fish and answering some questions regarding the symptoms. After the validation is over, a solution is presented along with a level of confidence. It treats six diseases. No evaluation of the system is reported.

3.3. Systems Using Fuzzy Logic

Fish-Vet is a diagnosis system for multiple fish diseases [40]. It uses a combination of rules and fuzzy logic for making diagnoses. The user selects the species, water type, and the symptoms observed in the fish. A diagnosis is run which results in a list of candidate diseases, where each disease is allocated a number indicating its distance from the most likely disease. This is performed by the rule-based component. All symptoms related to the diseases in the list are presented to the user and the user may reconsider their input symptoms. This is performed by the fuzzy logic module, which expands the list of symptoms via fuzzy relations. This is repeated two–three times until the second most likely candidate disease has a large enough distance from the most likely one. About 40 experts from 17 countries were used for the construction of the information and the knowledge included in the system. The authors admit that due to the generality of the system, its results are not always valid.

The Expert system for diagnosis of Discus fish disease [41] uses fuzzy rules for making decisions about Discus fish (Symphysodon Discus) diseases. It deals with nine diseases and five external clinical symptoms. The design of the representation and reasoning is based on two tables. The first is a disease–symptoms association table, where symptoms are distinguished in three physical and two behavioral signs. In the second table, each symptom is associated with three linguistic values corresponding to a measurable interval related to some symptoms. For example, symptom P2 is associated with the linguistic values: slight/some/severe, with corresponding "range values": 0–16/15–40/35–60, and "measurements": "fin section"/"the head and gills sections"/"whole body and bleeding". The linguistic values are assigned corresponding fuzzy sets and are used in the designed rules. Finally, 243 fuzzy rules were generated. The system architecture follows the standard one (Figure 2). The system was evaluated against experts using 31 images of diseased Discus fish. The expert system detected correctly the 28 cases, which results in an 90.32% accuracy.

3.4. Systems Using Case-Based Representation

The Case-Based Reasoning Model of the Fish Disease Diagnosis [42], although hybrid, is classified by us as a case-based reasoning system, given that CBR is its main framework, which matches its title too. Cases are created as the product of two matrices. One matrix (5×8) concerns five diseases and eight symptoms, and the other (8×5) concerns the symptoms and their weights in diagnosing the diseases. The system also includes a strong case-index mechanism. A rule base is used for case similarity checking. The symptoms mainly concern external clinical signs. No specific fish is mentioned. No evaluation of the system is reported.

The Aquatic Animal Disease Diagnosis System Based on Android [43] is an Android-based expert system for fish disease diagnosis, implemented in SQLite. It uses a case-based diagnostic reasoning combined with expert symptom scoring method. Both methods are used after the input of symptoms and their results are compared. If the results are different, the system shows the symptoms of both diseases to the user and asks for re-entering symptoms, until common results are produced. If the results are the same, then the case similarity metric is checked: its value should be between 0.65 and 0.95. If it is not, the user is asked either to accept it, despite the low similarity, or re-enter symptoms.

A pure CBR model is used in [44] for fish disease diagnosis. Knowledge elicited from experts and other sources was formulated in 10 cases concerning 6 diseases and 15 symptoms, mainly concerning external clinical signs, and considered as the golden cases. Euclidean distance metric is used for estimating case similarities. The system was evaluated with a set of 40 new cases and achieved an accuracy of 95% compared with the diagnosis results of an expert. There is no reference to specific fish. The case base looks quite simplistic.

3.5. Systems Based on Neural Networks

Artificial neural networks can also help in the development of an expert system for fish disease diagnosis, as in the case of the system in [45]. Two feedforward neural networks (NNs) were designed and trained using data provided by a University Laboratory in Brazil. The data concerned 12 bacterial diseases (43 external and internal clinical signs) and 8 protozoan diseases (28 external and internal clinical signs). The first NN dealt with bacterial diseases, had 43 inputs, 20 neurons in the hidden layer with sigmoid activation function, and 12 neurons in the output layer with linear activation function. The second dealt with protozoan diseases, had 28 inputs, 22 sigmoid neurons in the hidden layer, and 8 neurons with linear activation in the output layer. Thirty-one records of diagnosed diseases caused by bacteria were used for training (80%) and testing (20%) of the bacteria NN. Similarly, thirty records of diagnosed diseases caused by bacteria were used for training (80%) and testing (20%) of the protozoan NN. Both NNs performed with 97% accuracy on the test set.

The disease-diagnosis expert system based on artificial neural networks [46], also uses a neural network for fish disease diagnosis. Here, the basic idea is that old cases of fish disease are used to train the neural network, which then in turn makes the disease diagnosis. Firstly, the expert's diagnostic instances are stored and organized. Then, the learning algorithm is called to acquire important knowledge for the knowledge base. Each time new instances arrive, they are automatically studied and the knowledge base is updated. The users enter the symptoms that they observe on the fish and select the inference mechanism module. The inference mechanism queries the knowledge base and calculates the data. Finally, the results of the diagnosis are displayed by the Human Machine Interface.

3.6. Systems Using Hybrid Representations

SEDPA is an expert system for the diagnosis of eel (Anguilla) diseases, based on a hybrid representation and reasoning scheme [47]. The scheme combines ATN (Augmented Transition Net), a FLC (Fuzzy Logic Controller), and Dempster–Shafer Theory (DST). ATN accesses data stored in the domain database. It allows for the calculation of relative frequencies between pathologies, associated with the observed lesions/symptoms. FLC has two input fuzzy sets, the minimum relative frequency (MRF) for each symptom and the incidence of each one of the pathologies, and one output, the categorical belief level that one or more of the pathologies are responsible for the disease. SEDPA was evaluated against experts and its success rate was higher than the rates of the human experts. However, it cannot provide explanations.

Crab-Expert [48] is a web-based expert system for the diagnosis and treatment of crab (Brachyura) diseases. It uses an expert system shell, namely XF6.2, which facilitates knowledge acquisition from experts and offers a hybrid knowledge representation method, namely object-oriented knowledge body strategy. This combines rule-based and frame-based/object-based representation and reasoning. It provides a friendly user interface.

The expert system for fish disease diagnosis based on fuzzy neural network (FNN) [49] is used for diagnosing grass carp (Cyprinus carpio) disease. The system takes advantage of fuzzy logic representational capabilities and acquisition methods, as well as the reasoning mechanism, and combines them with the strong self-learning ability of neural networks. The fuzzy neural network consists of three modules. The first one is a module where values of disease symptoms are converted into fuzzy sets (values) represented by corresponding membership values. In other words, it is a fuzzification module. This module consists of two layers, an input layer and a quantitative input layer. The nodes of the first input layer represent the input variables which in turn represent the 10 symptoms, while the aim of the second one is to blur the input variables, that is to assign membership values. The second module, a learning reasoning module which is responsible for the diagnosis, consists of three layers of a back propagation neural network. These three layers are an input layer, where twenty-five membership values of the fuzzy module output are used as inputs; a hidden layer, having a smaller number of nodes; and an output layer, having seven neurons corresponding to seven diseases, where the membership values of the diseases are returned as outputs. Finally, the defuzzification module compares the largest membership value of disease with a threshold and if this value is greater than the threshold, the disease is diagnosed. It deals with 25 symptoms and 7 diseases. The symptoms include environmental, external, and internal symptoms.

3.7. Other Systems

The Two-Stage Fish Disease Diagnosis System [50] does not provide any explicit information about the technique(s) used to make the initial diagnosis, so we cannot classify the system according to that the techniques. The system works in two stages. In the first stage, a diagnosis is made based on environmental, external, and internal clinical signs, resulting in a set of candidate disease(s). If the first stage sub-system suggests so, then diagnosis proceeds to the second stage, where a final diagnosis is made based on microscopic image processing. It also provides a suitable treatment method and guidance for drug administration. The system deals with 14 diseases of olive flounder fish (platichthys flesus), which are distinguished in 5 bacterial, 3 parasitic, and 6 viral diseases. Only diagnosis of parasitic diseases may need to pass in the second stage. No evaluation is reported in the paper.

In Table 1, we present the above expert systems in terms of their technical and non-technical characteristics, to be able to make a comparison. NS means "not specified".

3.8. Discussion

From the above overview and Table 1 we can infer the following:

- Rules remain the basic AI method for fish disease diagnosis, completed with CFs or combined with other methods, such as fuzzy logic or CBR. This is due to the fact that full fish diagnosis data are not available, and experts remain the main source for knowledge acquisition;
- In systems that use CFs, authors usually consider the weights (the influence of a symptom in deriving the conclusion) of symptoms as CFs. However, this is not the right semantics of CFs (a weight does not denote the certainty of a symptom) and may lead to the wrong results. On the other hand, the certainty of a symptom is provided on the fly, when the system is running, not in advance;
- Additionally, the way which fuzzy values are produced in most of the systems that use fuzzy logic does not seem to be proper. For example, in the Expert system for the diagnosis of Discus fish disease [41], fuzzy values "slight", "some", and "severe" are used for a parameter called "wounds on body". To be able to construct corresponding fuzzy sets, the authors consider three "artificially" produced value ranges: "0–16", "15–40", and "35–60" that correspond to the "measurements": "fin section", "the head and gills section", and "whole body and bleeding", respectively, which are not really countable;
- Only three systems offer an explanation mechanism, all using a rule-based approach. Several of the systems, however, offer information about the diseases (symptoms, images), but they do not explain the current decision chain;
- Only one system includes image processing for identifying symptoms, but it does this only for microscopic image cases;
- Most of the systems consider a limited number of symptoms for making diagnoses; they usually consider only external symptoms, which lead to quite approximate conclusions;
- None of them considers modern diagnostic methods for almost certain diagnoses, such as molecular techniques;
- None of them seems to make diagnoses for all disease categories. The most common categories are bacterial and parasitic diseases;
- More than half the systems are dedicated to a specific fish. This makes their diagnoses more accurate. All of them are freshwater fish, due to the Chinese origin of the corresponding research;
- Most of them do not provide a treatment proposal;
- Most of them have not been systematically evaluated.

Table 1. Expert Systems for Fish Disease Diagnosis from 2000 to 2022.

ES	Method	Explanation	Image Process	Water Type	Parameters	Diseases	Fish Type	Treatment	Evaluation
Fish-Vet [40], 2000	Rules and fuzzy logic	No	No	NS	External, Internal	NS	General	No	No
Fish-Expert [34], 2002	Rules	Yes	No	Fresh	All except Molecular	126 (NS)	Nine fish (NS)	Yes	No
SEDPA [47], 2005	Hybrid (ATN, Fuzzy logic, DST)	No	No	Both	External	NS	Eel (Anguilla)	No	Yes
Crab-Expert [48], 2006	Hybrid (rules and objects)	No	No	Marine	All except molecular	NS	Crab (Brachyura)	Yes	No
CBR Model [42], 2009	CBR (with rules)	No	No	NS	External	Five	General	No	No
FIDSS [37], 2009	Rules with CFs	No	No	NS	NS	NS	General	No	No
NN Model [45], 2011	Neural Net	No	No	NS	NS	Bacterial, Protozoan	General	No	Yes
Two-Stage Model [50], 2011	Not explicitly specified	No	Yes	NS	All except molecular	Bacterial, Parasitic, Viral	Olive Flounder (Platichthys flesus)	Yes	No
FNN Model [49], 2012	Hybrid (FNN)	No	No	Fresh	10 symptoms (NS)	Seven diseases	Grass Carp (Cyprinus carpio)	No	No
NN Model [46], 2013	Neural Net	No	No	NS	8 symptom classes	Eight diseases	General	No	Yes
Discus fish [41], 2015	Fuzzy rules	No	No	Fresh	External	Nine diseases	Discus (Symphysodon Discus)	No	Yes
Aquatic Animal [43], 2016	Case-Based	No	No	NS	NS	NS	NS	No	No
Catfish [38], 2017	Rules with CFs	No	No	Fresh	External (16)	Seven diseases	Catfish (Silurus glanis)	No	No
Koi fish [39], 2018	Rules with CFs	Yes	No	Fresh	External (15)	Six diseases	Koi fish (Cyprinus carpio haematopterus)	No	No
CBR Model [44], 2021	CBR	No	No	NS	External (15)	Six diseases	General	No	Yes
Betta fish [35], 2021	Rules	No	No	Fresh	External (15)	Seven diseases: Parasitic, Bacterial, Fungal	Betta fish (Betta splendens)	No	No
Catfish [36], 2022	Rules	Yes	No	Fresh	External (27)	Bacterial, Parasitic	Catfish (Silurus glanis)	No	No

4. Proposed System Architecture

The "Fish AI" project (www.fishai.upatras.gr, accessed on 21 April 2023) is a collaboration of three Greek universities and two fish farms aiming at the improvement of the competitiveness of Greek fish farming through innovative actions to the whole production process. An intelligent system for the diagnosis of fish diseases in Mediterranean fish farms is under development, which will provide a simultaneous response to the issues of treatment and drug information. The system deals with the diseases of the two major farmed fish species: sea bass and sea bream [51,52]. Four experts have been interrogated for knowledge acquisition and other sources have been studied. Based on the knowledge acquisition results and the above overview of expert systems, we present here the proposed architecture (Figure 7) and the diagnosis process flow (Figure 8) of our system.

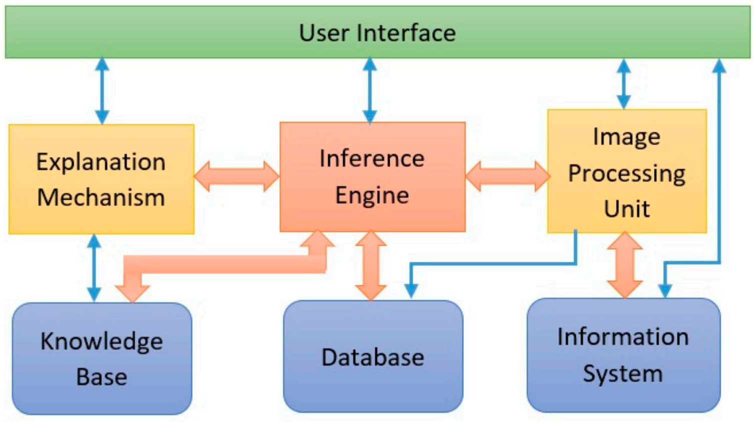

Figure 7. Proposed Expert System Architecture.

According to the architecture in Figure 7, our system consists of six units: Inference Engine (IE); Knowledge Base (KB); Database (DB); Explanation Mechanism (EM); Image Processing Unit (IPU); and Information System (IS). KB consists of rules with CFs (each rule has a CF provided by the experts). DB is used for storing data provided by the user, results (intermediate or final) produced by the IE using the rules in KB, and results from IPU. EM gives explanations about the reasoning that reached a diagnosis, whereas IPU uses image processing techniques to extract values for internal or external symptoms from corresponding fish images, as well as results from microscopic images. Image matching techniques or ML techniques could be used here. IS is an e-learning system that includes material about fish diseases (diseases, symptoms, images, decision trees), as well as stuff for learning the use of the expert system.

In Figure 8, the flowchart of the fish disease diagnosis process to be implemented by the expert system is presented. Diagnosis is made in five stages (levels). Each stage gives an increased certainty diagnosis. Each level diagnosis is based on an increased number of symptoms or parameters. Therefore, a fish farm can use it as far as its technical and human resources allow.

At the first level, only environmental parameters, such as water temperature or the fish growth phase (represented by its weight class), are considered. These parameters can exclude some of the possible diseases; therefore, the rest are provided as its output, ordered according to their CFs. It may happen that it is adequate in some cases. If it is not, then the process goes to the next level, where external symptoms of the fish are considered. If an image of the fish concerning external features (such as the body, head, tail, etc.) is available, then the IP unit takes over and produces values for the involved parameters. Otherwise, the human-user gives those values by observation. After that, a revised list of possible diseases is presented to the user. If the result is still not satisfying, e.g., because more than one disease is diagnosed and/or the achieved CFs do not have adequately high values, the system (selected by the human-user) proceeds to the third level.

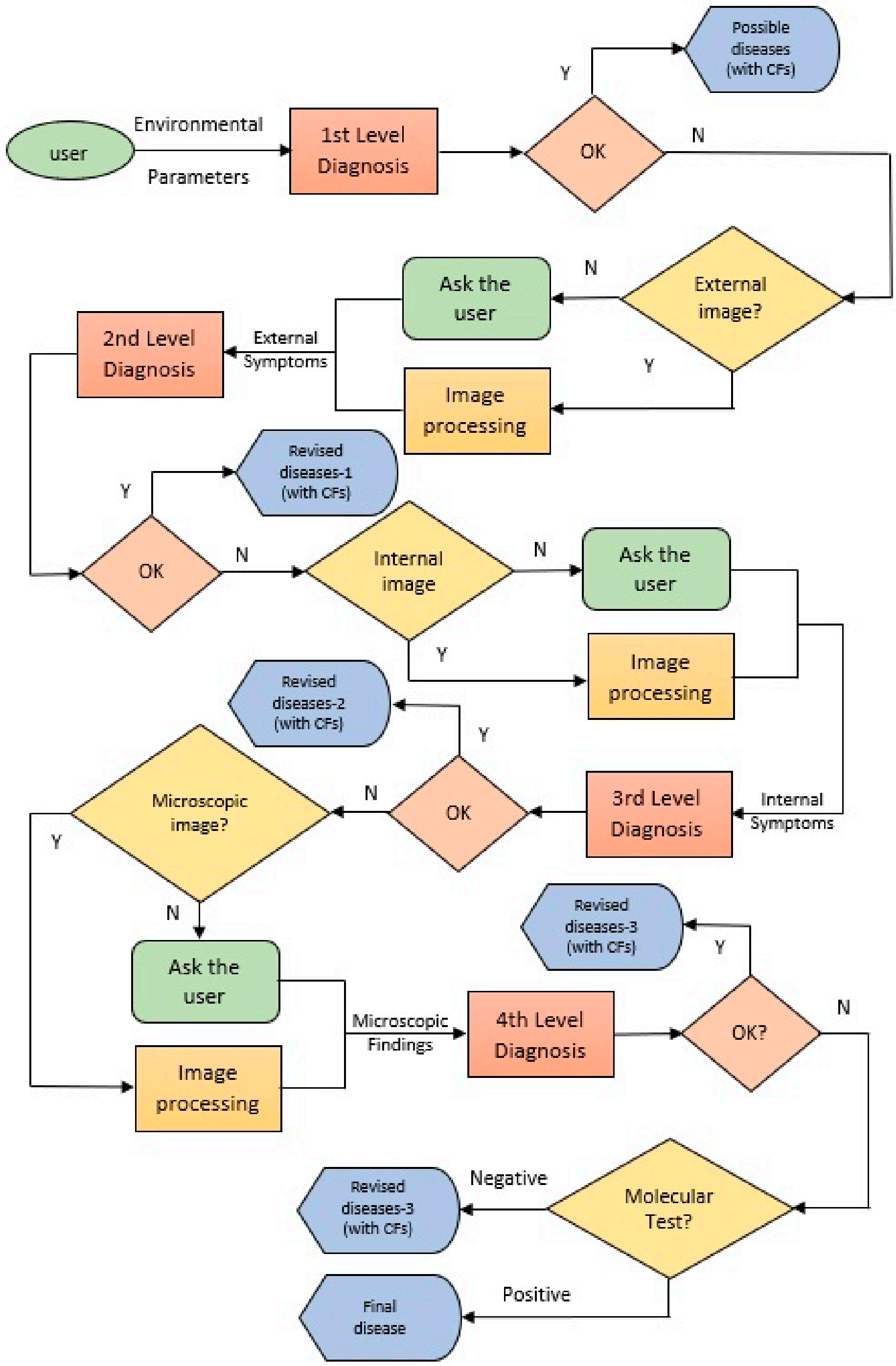

Figure 8. The diagnosis process flowchart.

At the third level, internal symptoms are used for diagnosis. If an image of the fish concerning internal features (image of a dissected fish) is available, then the IP unit takes over and produces values for the involved parameters. Otherwise, the human-user gives those values by observation. After that, a third revised list of possible diseases is presented to the user. If the result is still not satisfying, e.g., because more than one disease is diagnosed, and/or achieved CFs have not adequately high values, the system (selected by the human-user) proceeds to the fourth level.

The decision of the user to proceed to the fourth level is based on a shortage of resources (microscope), urgency, or cost. At the fourth level, the microscopic result is considered too, either using the IP unit or the opinion of an expert-user (observing through the microscope). This, depending on the findings, may lead to the last level, where final diagnosis is made through a molecular test (e.g., PCR). A factor for proceeding or not to the last level is the cost in time and money.

5. Conclusions

This paper presents an overview of expert systems for farmed fish disease diagnosis and treatment. The overview specifies important technical and non-technical characteristics of the existing systems. Based on them, we propose an expert system architecture that includes all components necessary for the complete diagnoses of fish diseases. It can handle symptoms related to both image and non-image data. The symptoms related to non-image data are explored by the user-expert of the system. The symptoms related to image data can be alternatively explored either by the user-expert or by an image processing unit that uses pattern matching or machine learning techniques. In addition, the diagnosis process is level wise, and proceeds from low certainty decisions (based on environmental parameters) to higher certainty ones, going through four consecutive decision levels. At each level, more parameters/symptoms are considered (from clinical to cellular and then to molecular). Rules with some kind of CFs is the proposed knowledge representation and reasoning scheme. The diagnosis process can stop at any level, where a list of possible diseases is displayed to the user, ordered by their CFs, given the satisfiability of the user and/or the shortage of further evidence. Explanations may be provided at any stage of the reasoning process.

Our further work consists of (a) a more detailed specification of the architecture and the diagnosis process, and (b) the implementation of the resultant system and diagnosis process for sea bass and sea bream.

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References

1. Naylor, R.L.; Hardy, R.W.; Buschmann, A.H.; Bush, S.R.; Cao, L.; Klinger, D.H.; Little, D.C.; Lubchenco, J.; Shumway, S.E.; Troell, M. A 20-year retrospective review of global aquaculture. *Nature* **2021**, *591*, 551–563, Erratum in *Nature* **2021**, *593*, E12; Erratum in *Nature* **2021**, *595*, E36. [CrossRef]
2. Bogard, J.R.; Farmery, A.K.; Little, D.C.; Fulton, E.A.; Cook, M. Will fish be part of future healthy and sustainable diets? *Lancet Planet. Health* **2019**, *3*, e159–e160. [CrossRef] [PubMed]
3. Farmery, A.K.; Gardner, C.; Jennings, S.; Green, B.S.; Watson, R.A. Assessing the inclusion of seafood in the sustainable diet literature. *Fish Fish.* **2017**, *18*, 607–618. [CrossRef]
4. Thilsted, S.H.; Thorne-Lyman, A.; Webb, P.; Bogard, J.R.; Subasinghe, R.; Phillips, M.J.; Allison, E.H. Sustaining healthy diets: The role of capture fisheries and aquaculture for improving nutrition in the post-2015 era. *Food Policy* **2016**, *61*, 126–131. [CrossRef]
5. Alagappan, M.; Kumaran, M. Application of expert systems in fisheries sector. *Res. J. Anim. Vet. Fish. Sci.* **2013**, *1*, 19–30.
6. Freitas, J.; Vaz-Pires, P.; Câmara, J.S. From aquaculture production to consumption: Freshness, safety, traceability and authentication, the four pillars of quality. *Aquaculture* **2020**, *518*, 734857. [CrossRef]
7. Zion, B. The use of computer vision technologies in aquaculture—A review. *Comput. Electron. Agric.* **2012**, *88*, 125–132. [CrossRef]

8. Mustapha, U.F.; Alhassan, A.-W.; Jiang, D.-N.; Li, G.-L. Sustainable aquaculture development: A review on the roles of cloud computing, internet of things and artificial intelligence (CIA). *Rev. Aquac.* **2021**, *13*, 2076–2091. [CrossRef]
9. Sánchez, J.L.F.; Le Breton, A.; Brun, E.; Vendramin, N.; Spiliopoulos, G.; Furones, D.; Basurco, B. Assessing the economic impact of diseases in Mediterranean grow-out farms culturing European sea bass. *Aquaculture* **2022**, *547*, 737530. [CrossRef]
10. Maldonado-Miranda, J.J.; Castillo-Perez, L.J.; Ponce-Hernandez, A.; Carranza-Alvarez, C. Chapter 19—Summary of economic losses due to bacterial pathogens in aquaculture industry. In *Bacterial Fish Diseases*; Academic Press: Cambridge, MA, USA, 2022; pp. 39–417.
11. Theodorou, J.A.; Kotsonis, A.; Sorgeloos, P.; Viaene, J.; Tzovenis, I. Risk assessment of seabass and seabream aquaculture based on insurance claims in Greece. In *Proceedings of the Fifteenth Biennial Conference of the International Institute of Fisheries Economics & Trade, 13–16 July 2010, Montpellier, France: Economics of Fish Resources and Aquatic Ecosystems: Balancing Uses, Balancing Costs. Compiled by Ann L. Shriver*; International Institute of Fisheries Economics & Trade: Corvallis, OR, USA, 2010; ISBN 0-9763432-6-6.
12. Zrncic, S. *Diagnostic Manual for the Main Pathogens in European Seabass and Gilthead Seabream Aquaculture*; Options Méditerranéennes, Series B: Studies and Research, No. 75; CIHEAM: Zaragoza, Spain, 2020; 172p.
13. Li, D.; Li, X.; Wang, Q.; Hao, Y. Advanced Techniques for the Intelligent Diagnosis of Fish Diseases: A Review. *Animals* **2022**, *12*, 2938. [CrossRef] [PubMed]
14. Zhao, S.; Zhang, S.; Liu, J.; Wang, H.; Li, D.; Zhao, R. Application of machine learning in intelligent fish aquaculture: A Review. *Aquaculture* **2021**, *540*, 736724. [CrossRef]
15. Ahmed, S.; Aurpa, T.T.; Azad, A.K. Fish Disease Detection Using Image Based Machine Learning Technique in Aquaculture. *J. King Saud Univ. Comput. Inf. Sci.* **2022**, *34*, 5170–5182. [CrossRef]
16. Chary, K.; Brigolin, D.; Callier, M.D. Farm-scale models in fish aquaculture – An overview of methods and applications. *Rev. Aquac.* **2022**, *14*, 2122–2157. [CrossRef]
17. Sun, M.; Yang, X.; Xie, Y. Deep Learning in Aquaculture: A Review. *J. Comput.* **2020**, *31*, 294–319.
18. Negnevitsky, M. *Artificial Intelligence—A Guide to Intelligent Systems*, 3rd ed.; Pearsons Higher Education: New York, NY, USA, 2010.
19. Grosan, C.; Abraham, A. *Intelligent Systems—A Modern Approach*; Springer: Berlin/Heidelberg, Germany, 2011.
20. Shortliffe, E.H.; Buchanan, B.G. A model of inexact reasoning in medicine. *Math. Biosci.* **1975**, *23*, 351–379. [CrossRef]
21. Konstantinopoulou, G.; Kovas, K.; Hatzilygeroudis, I.; Prentzas, J. An Approach using Certainty Factor Rules for Aphasia Diagnosis. In Proceedings of the 10th International Conference on Information, Intelligence, Systems and Applications (IISA 2019), Patras, Greece, 15–17 July 2019.
22. Zadeh, L. Fuzzy sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]
23. Kolodner, J.L. *Case-Based Reasoning*; Morgan Kaufmann: San Mateo, CA, USA, 1993.
24. Richter, M.M.; Weber, R.O. *Case Based Reasoning—A Textbook*; Springer: Heidelberg, Germany; New York, NY, USA; Dordrecht, The Netherlands; London, UK, 2013.
25. Aamodt, A.; Plaza, E. Case-based reasoning: Foundational issues, methodological variations and system approaches. *Artif. Intell. Commun.* **1994**, *7*, 39–59. [CrossRef]
26. Prentzas, J.; Hatzilygeroudis, I. Categorizing Approaches Combining Rule-Based and Case-Based Reasoning. *Expert Syst.* **2007**, *24*, 97–122. [CrossRef]
27. Chatzilygeroudis, K.; Perikos, I.; Hatzilygeroudis, I. Machine Learning Basics. In *Intelligent Computing for Interactive System Design: Statistics, Digital Signal Processing, and Machine Learning in Practice*; Eslambolchilar, P., Komninos, A., Dunlop, M., Eds.; ACM: New York, NY, USA, 2021; pp. 143–193. [CrossRef]
28. Aggarwal, C.C. *Neural Networks and Deep Learning: A Textbook*; Springer International Publishing AG: New York, NY, USA, 2018.
29. Rumelhart, D.E.; Hinton, G.E.; Williams, R.J. Learning internal representations by error propagation. *Parallel Distrib. Process. Explor. Microstruct. Cogn.* **1986**, *1*, 316–362.
30. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [CrossRef] [PubMed]
31. Ruder, S. An overview of gradient descent optimization algorithms. *arXiv* **2017**, arXiv:1609.04747. [CrossRef]
32. Moreira, M.; Schrama, D.; Farinha, A.P.; Cerqueira, M.; de Magalhães, C.R.; Carrilho, R.; Rodrigues, P. Fish Pathology Research and Diagnosis in Aquaculture of Farmed Fish; a Proteomics Perspective. *Animals* **2021**, *11*, 125. [CrossRef] [PubMed]
33. MacAulay, S.; Ellison, A.R.; Kille, P.; Cable, J. Moving towards improved surveillance and earlier diagnosis of aquatic pathogens: From traditional methods to emerging technologies. *Rev. Aquac.* **2022**, *14*, 1813–1829. [CrossRef] [PubMed]
34. Li, D.; Fu, Z.; Duan, Y. Fish-Expert: A web-based expert system for fish disease diagnosis. *Expert Syst. Appl.* **2002**, *23*, 311–320. [CrossRef]
35. Mardiyanto, M.; Fahmi, F.; Satria, F. Expert System for Diagnosis Diseases in Betta Fish Based on Android. *Int. J. Artif. Intell. Robot. Technol.* **2021**, *1*, 35–44.
36. Riyanto, E.D.; Prasetyo, E.; Zainal, R.F.; Rubaningtyas, R.; Setyatama, F.; Herulambang, W.; Alim, S.; Tias, R.F. Design of Expert System Diagnosis of Catfish Disease with Forward Chaining Method. *J. Electr. Eng. Comput. Sci.* **2022**, *7*, 1215–1222. [CrossRef]
37. Zhang, X.; Fu, Z.; Cai, W.; Tian, D.; Zhang, J. Applying evolutionary prototyping model in developing FIDSS An intelligent decision support system for fish disease/health management. *Expert Syst. Appl.* **2009**, *36*, 3901–3913. [CrossRef]
38. Sumartono, I.; Arisandi, D.; Siahaan, A.P.U.; Aan, M. Expert System of Catfish Disease Determinant Using Certainty Factor Method. *Int. J. Recent Trends Eng. Res.* **2017**, *3*, 202–209. [CrossRef]

39. Fahrozi, W.; Harahap, C.B.; Syahputra, A.; Pane, R. Expert System of Diagnosing Koi's Fish Disease by Certainty Factor Method. In Proceedings of the 2018 6th International Conference on Cyber and IT Service Management (CITSM), Parapat, Indonesia, 7–9 August 2018; pp. 1–5. [CrossRef]
40. Zeldis, D.; Prescott, S. Fish disease diagnosis program—Problems and some solutions. *Aquac. Eng.* **2000**, *23*, 3–11. [CrossRef]
41. Hanafiah, N.; Sugiarto, K.; Ardy, Y.; Prathama, R.; Suhartono, D. Expert system for diagnosis of Discus fish disease using fuzzy logic approach. In Proceedings of the 2015 IEEE International Conference on Computer and Communications (ICCC), London, UK, 8–12 June 2015; pp. 56–61. [CrossRef]
42. Fu, Z.; Hong, G.; Sun, J. Case-Based Reasoning Model of the Fish Disease Diagnosis. In *Computer and Computing Technologies in Agriculture II, Volume 2, IFIP*; Li, D., Chunjiang, Z., Eds.; Springer: Boston, MA, USA, 2009; Volume 294, pp. 1433–1442.
43. Sun, M.; Li, D. Aquatic Animal Disease Diagnosis System Based on Android. In Proceedings of the 9th IFIP WG 5.14 International Conference on Computer and Computing Technologies in Agriculture (CCTA), Beijing, China, 27–30 September 2016; pp. 115–124.
44. Tomatala, M.F.; Arundaa, R.; Damodalag, H. Fish Disease Diagnosis using Case-based Reasoning with Euclidean Distance. In *Proceedings of the 4th International Conference of Vocational Higher Education (ICVHE 2019)—Empowering Human Capital Towards Sustainable 4.0 Industry*; SCITEPRESS-Science and Technology Publications, LDA: Setúbal, Portugal, 2021; pp. 215–221.
45. Lopes, J.N.S.; Concales, A.N.A.; Fujimoto, R.Y.; Carvalho, J.C.C. Diagnosis of Fish Disease Using Artificial Neural Networks. *Int. J. Comput. Sci. Issues* **2011**, *8*, 68.
46. Deng, C.; Wang, W.; Gu, J.; Cao, X.; Ye, C. Research of fish disease diagnosis expert system based on artificial neural networks. In Proceedings of the 2013 IEEE International Conference on Service Operations and Logistics, and Informatics, Dongguan, China, 28–30 July 2013; pp. 591–595. [CrossRef]
47. Gutierrez-Estrada, J.C.; De Pedro Sanz, E.; Lopez-Luque, R.; Pulido-Calvo, I. SEDPA, an expert system for disease diagnosis in eel rearing systems. *Aquac. Eng.* **2005**, *33*, 110–125. [CrossRef]
48. Yuan, H.; Yang, Y.; Chen, Y. Crab-Expert: A Web-Based ES for Crab Farming. In Proceedings of the 2006 9th International Conference on Control, Automation, Robotics and Vision, Singapore, 5–8 December 2006; pp. 1–5. [CrossRef]
49. Gu, J.; Deng, C.; Lin, X.; Yu, D. Expert system for fish disease diagnosis based on fuzzy neural network. In Proceedings of the 2012 Third International Conference on Intelligent Control and Information Processing, Dalian, China, 15–17 July 2012; pp. 146–149. [CrossRef]
50. Han, C.-M.; Lee, S.-W.; Han, S.; Park, J.-S. Two-Stage Fish Disease Diagnosis System Based on Clinical Signs and Microscopic Images. In *ICCSA 2011, Part II, LNCS 6783*; Mugrante, B., Gervasi, O., Iglesias, A., Taniar, D., Apduhan, B.O., Eds.; Springer: Berlin/Heidelberg, Germany, 2011; pp. 635–647.
51. Theodorou, J. Current & Future Technological Trends of European Seabass-Seabream Culture. *Rev. Fish. Sci.* **2002**, *10*, 529–543.
52. Theodorou, J.A.; Perdikaris, C.; Filippopoulos, N.G. Evolution Through Innovation in Aquaculture: The Case of the Hellenic Mariculture Industry (Greece). *J. Appl. Aquac.* **2015**, *27*, 160–181. [CrossRef]