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Automobile Fault Diagnosis System with Expert System and Neural Network Tools

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ABSTRACT

Research has shown that traditional diagnostic technologies could not meet all the requirements of fault detection and maintenance in automobile systems due to product variety and structure complexity of automobiles. To improve the diagnosis and maintenance level of automobile faults, Artificial Neural Network (ANN) and Expert System technology were applied. ANN simulates the human brain to achieve artificial intelligence and response from a large number of captured events. It usually involves a large number of processors operating in parallel, each with its own small sphere of knowledge and access of data in its local memory. The case of abnormal noise of automobile engine, the typical fault phenomenon of abnormal sound is analyzed in detail. An automobile fault diagnosis expert system based on three-layer neutral network was designed and implemented. The results obtained showed that the proposed system will diagnose fault in automobile system effectively.

Keywords: Expert Systems, Artificial Neural Networks, Fault Diagnosis, Automobile.

Aims Research Journal Reference Format:
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1. INTRODUCTION

The desire to get trendy cars give a drastic increase to the total number of vehicle in Nigeria. The automobile models are complex, the types are diverse, the internal structures are complicated and the different faults are difficult to be found. Many automobile maintenance enterprises cannot repair the faults or meet the maintenance needs due to lack of technical guidance of experts. In order to improve the utilization rate of vehicle and reduce the economic losses, the users want to have convenient automobile fault detection methods and understand the real-time usage states. The expert system is one of the most important and active application areas of artificial intelligence. It is an intelligent computer program based on knowledge, using expertise of human expert to solve complex problems in certain fields. The expert system developed for automobile fault diagnosis can simulate diagnostic ideas of maintenance experts to find and remove automobile troubles. The system mainly uses the build-in-vehicle sensors to obtain fault information of electronics control units. It makes use of artificial intelligence algorithm to process the obtained comprehensive fault information, analyzes the causes of failures and report the analysis results to the users. The fault diagnostic objects include engine, chassis, electrical equipment and so on. Fault diagnosis is an important application direction of artificial intelligence in automobile industry and it is the product of collaboration of field experts and engineers.
This study therefore analyzes the characteristics of expert system, the design of automobile fault diagnosis expert system centered on neural network technology and the intelligent fault diagnosis is implemented.

2. MODELS FOR AUTOMOBILE FAULT DIAGNOSIS

There are several existing models for automobile fault diagnosis expert system. They include rule-based diagnosis expert system, instance-based diagnosis expert system, behavior-based diagnosis expert systems, fuzzy logic - based diagnosis expert systems and artificial neural network-based diagnosis expert system. Although the research of fault diagnosis expert system for automobiles had made some progress but it still cannot fully replace the thought process of experts. It is necessary that the system should cooperate with experts in fault diagnosis field to obtain satisfactory diagnostic results.

There are different ways in which data can be transformed and presented as a priori knowledge to a diagnostic system. This is known as feature extraction. This extraction process can either be qualitative or quantitative in nature. Two of the major methods that extract qualitative history information are the expert systems and trend modeling methods. Methods that extract quantitative information can be broadly classified as non-statistical or statistical methods. Neural networks are important class of non-statistical classifiers. Principal Component Analysis (PCA) / Partial Least Squares (PLS) and statistical pattern classifiers form a major component of statistical feature extraction methods. The different ways in which knowledge can be extracted from process history are schematically presented in Fig. 1.

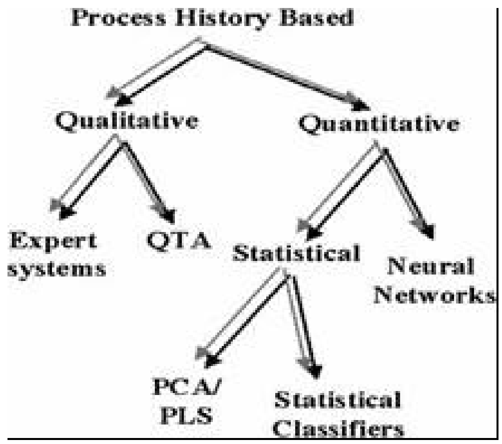

Fig. 1: Knowledge Extraction
(Source: Venkatasubramanian *et al.,* 2003)

2.1 Qualitative Feature Extraction
This section reviews the methods that employ qualitative feature extraction. ng approaches.

2.1.1 Expert Systems
Rule-based feature extraction had been widely used in expert systems for many applications. An expert system is generally a very specialized system that solves problems in a narrow domain of expertise. The main components in an expert system development include: knowledge acquisition, choice of knowledge representation, the coding of knowledge in a knowledge base, the development of inference procedures for diagnostic reasoning and the development of input/output interfaces. The main advantages of the development of expert systems for diagnostic problem-solving are: ease of development, transparent reasoning, the ability to reason under uncertainty and the ability to provide explanations for the solutions provided. Review of literature on the application of expert systems for fault diagnosis can be found in Chester *et al*. (1984) and Niida (1985). Rich *et al*., (1989) discussed diagnostic expert system for a whipped topping process. The objectives of expert system were two fold. Firstly, the system classifies the reasons for the observed problem as an operator error, equipment failure or system disturbance. Secondly, the expert system offers prescriptive remedies to restore the process to normal operation.

Structuring the knowledge-base through hierarchical classification was studied Ramesh *et al*., (1988) and an application of an expert system for catcracker diagnosis can be found in Ramesh *et al.,* (1989). Several large systems have been built using such an approach and constitute an improvement over the unstructured rule-based systems. Ideas on knowledge-based diagnostic systems based on the task framework can be found in Ramesh *et al.,* (1992). A rule-based expert system for fault diagnosis in a cracker unit is described in Venkatasubramanian (1989) and a specialized shell for diagnostic expert systems can be found in Venkatasubramanian (1988). A discussion on different forms of reasoning in expert systems can be found in Ungar and Venkatasubramanian (1990). More work on expert systems in fault diagnosis can be found in Quantrille and Liu (1991). A framework to represent the uncertain elements of the diagnostic problem using belief networks, and the use of distributed network (parallel) computations to determine the most probable diagnostic hypotheses can be found in Guzman and Kramer (1993).

Basila *et al.* (1990) developed a supervisory expert system that uses object based knowledge representation to represent heuristic and model-based knowledge. Zhang and Roberts (1991) presented a methodology for formulating diagnostic rules from the knowledge of system structures and component functions. Chen and Modarres (1992) developed an expert system, called FAX, to address the determination of the root cause of process malfunctions and suggestions for corrective action(s) to avert abnormal situations. Becraft and Lee (1993) proposed an integrated framework comprising of a neural network and an expert system. A neural network is used as a first-level filter to diagnose the most commonly encountered faults in chemical process plants. Once the faults are localized within a particular process by the neural network, a deep knowledge expert system analyzes the result, and either confirms the diagnosis or else offers an alternative solution. Tarifa and Scenna (1997) proposed a hybrid system that uses Signed Directed Graphs (SDG) and fuzzy logic. The SDG model of the process is used to perform qualitative simulation to predict possible process behaviors for. There are a number of other papers that discuss specific applications of expert systems for fault diagnosis. However, in all the applications, the limitations of an expert system approach are obvious. Knowledge-based systems developed from expert rules are very system specific, their representation power is quite limited, and they are difficult to update Rich and Venkatasubramanian, (1987). The advantage though is the ease of development and transparent reasoning.

2.1.2 Qualitative Trend Analysis (QTA)

A second approach to qualitative feature extraction is the abstraction of trend information. Trend analysis and prediction are important components of process monitoring and supervisory control. Trend modeling can be used to explain the various important events happening in the process, do malfunction diagnosis and predict future states. From a procedural perspective, in order to obtain a signal trend not too susceptible to momentary variations due to noise, some kind of filtering needs to be employed. For example, time series representations assume, a priori, certain behavior as they are identified using a known process behavior. Alternatively, one may simply use a filter (such as an auto-regressive filter) with a priori chosen filter coefficients (specifying the required degree of smoothing). Both types of filters suffer from the fact that they cannot distinguish well between a transient and true instability Gertler, (1989). The essential qualitative characters might be distorted by these filters. Avoiding this problem requires that the trend be viewed from different time scales or different levels of abstraction. Qualitative abstraction allows for a compact representation of the trend by representing only the significant events. For tasks such as diagnosis, qualitative trend representation often provides valuable information that facilitates reasoning about the process behavior. In a majority of cases, process malfunctions leave a distinct trend in the sensors monitored. These distinct trends can be suitably utilized in identifying the underlying abnormality in the process. Thus, a suitable classification and analysis of process trends can detect the fault earlier and lead to quick control. Also, qualitative trend representation can pave way for efficient data compression.

Cheung and Stephanopoulos (1990) built a formal framework for the representation of process trends. They introduced triangulation to represent trends. Triangulation is a method where each segment of a trend is represented by its initial slope, its final slope (at each point, or critical point of the trend) and a line segment connecting the two critical points. A series of triangles constitute a process trend. Through this method, the actual trend always lies within the bounding triangle, which illustrates the maximum error in the representation of the trend. Rengaswamy and Venkatasubramanian (1995) shown how primitives can be extracted from raw noisy sensor data by treating the problem of primitive identification as a classification problem using neural networks. Each data set in a given time window was classified as one of the primitives. Vedam and Venkatasubramanian (1997) proposed a wavelet theory based adaptive trend analysis framework and later proposed a dyadic B-Spines based trend analysis algorithm Vedam *et al*., (1998). Rengaswamy *et al.,* (2001) discussed the utility of trend modeling in control loop performance assessment. Konstantinov and Yoshida (1992) proposed a qualitative analysis procedure with the help of an expandable shape library that stores shapes like decreasing concavely, decreasing convexly and so on. Whiteley and Davis (1992) discussed qualitative interpretations from sensor data as an adaptive pattern recognition problem.

2.2 Quantitative Feature Extraction

The quantitative approaches essentially formulate the diagnostic problem-solving as a pattern recognition problem. The goal of pattern recognition is the classification of data points to, in general, pre-determined classes. Statistical methods use knowledge of a priori class distributions to perform classification. An example is a Bayes classifier which uses the density functions of the respective classes. Approaches like PCA, on the other hand, extract information about major trends in the data using a small number of relevant factors. Neural networks assume a functional form for the decision rule thus parameterizing the classifier.

3. ARTIFICIAL NEURAL NETWORK (ANN)

Neuron is the basic unit of neural network which can be regarded as a multi-input single-output nonlinear device and its internal state is determined by the weighted sum of the input signals (Li, 1999). Neural network consists of many neurons which are arranged in layers. According to their connection methods, from the functional point of view, the neural network is divided into two types, feed forward network and feedback network.

3.1 Feed forward neutral network

Feed forward network is the most common type which system structure is shown in Fig.2

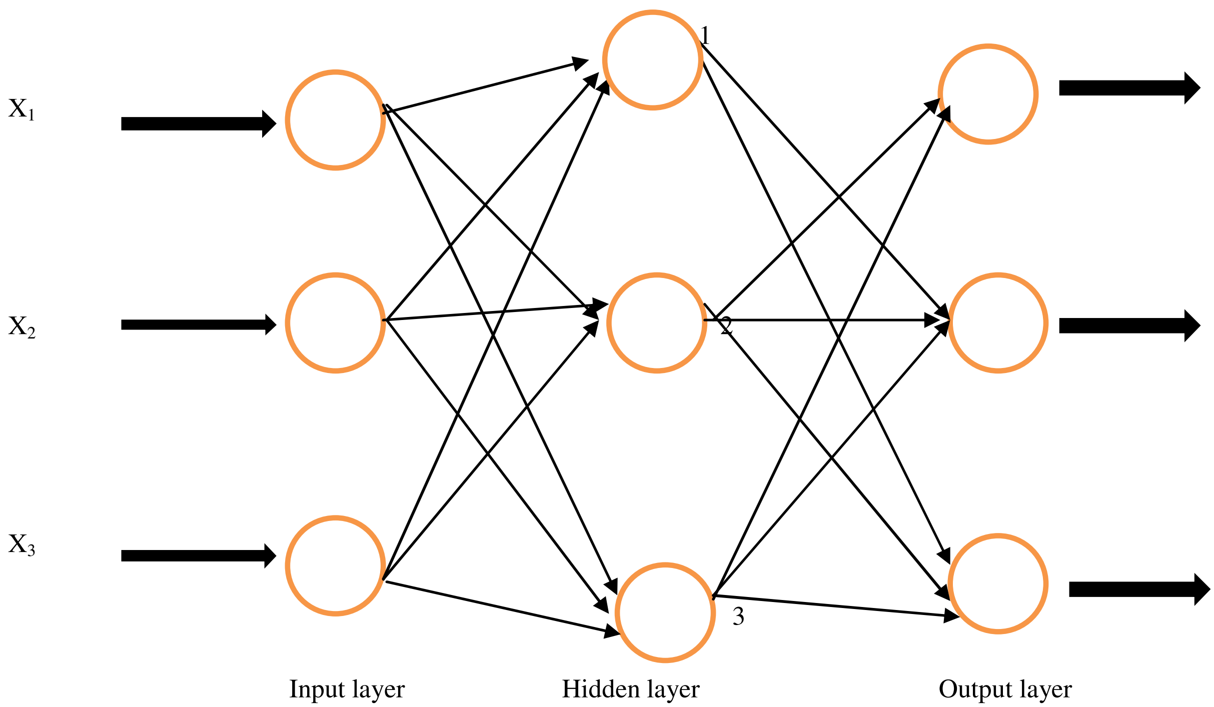

Fig 2: Feed forward neural network

Each neuron in the network receives the inputs of previous level and output to the next level, the network has no feedback. The network nodes are classified into two categories: Input unit and calculating unit. Each calculating unit may have any number of inputs but only one output. Usually, the feed forward network can be divided into different layers. The inputs of layer i are only connected with the outputs of layers i-1. The input and output nodes of system are connected to the outside, while the other intermediate layers are called hidden layers. All layers constitute a strong learning system which structure is simple and easy to be programmed. From a system point of view, the feed forward network is static non-linear mapping. Most of feed forward neural networks do not pay attention to the dynamic behaviour of the system. Their capabilities of classification and pattern recognition are stronger than other types of neural networks.

3.2 Feedback neutral network

Feedback neural network is also known as recursive network or regression network. In the feedback network, the input signal determines the initial state of the feedback system. After a series of state transitions, the system gradually converges to an equilibrium state. It follows that the stability of the feedback network is one of the most important issues. All nodes of feedback neural network are calculating units. They can receive inputs and also output to the outside.

3.3 Back Propagation (BP) neural network

The artificial neural networks are widely used in pattern recognition and other fields and the most used one is BP neutral network Wu *et al*., (2008) which is a multilayer feed forward network and can be used in fault diagnosis fields. Usually, the action function of neurons mostly is Sigmoid function. With its conductivity, the leases mean squares learning algorithm is introduced, that is, in the learning process of neural network, the error between actual network output and desired output spreads backward when correcting connected strength to minimize the mean square value of error Jiaqiang, (2006). Neural network is based on logical reasoning, going through knowledge acquisition, knowledge representation, knowledge reasoning and other stages and it should take long time. Neural network simulates human brain to achieve artificial intelligence and respond from a large number of captured events.

3.4 Neuro-Expert System

The basic structure of neuro-network expert system is shown in Fig. 3. It can automatically obtain the module input, organize and store learning examples provided by expert

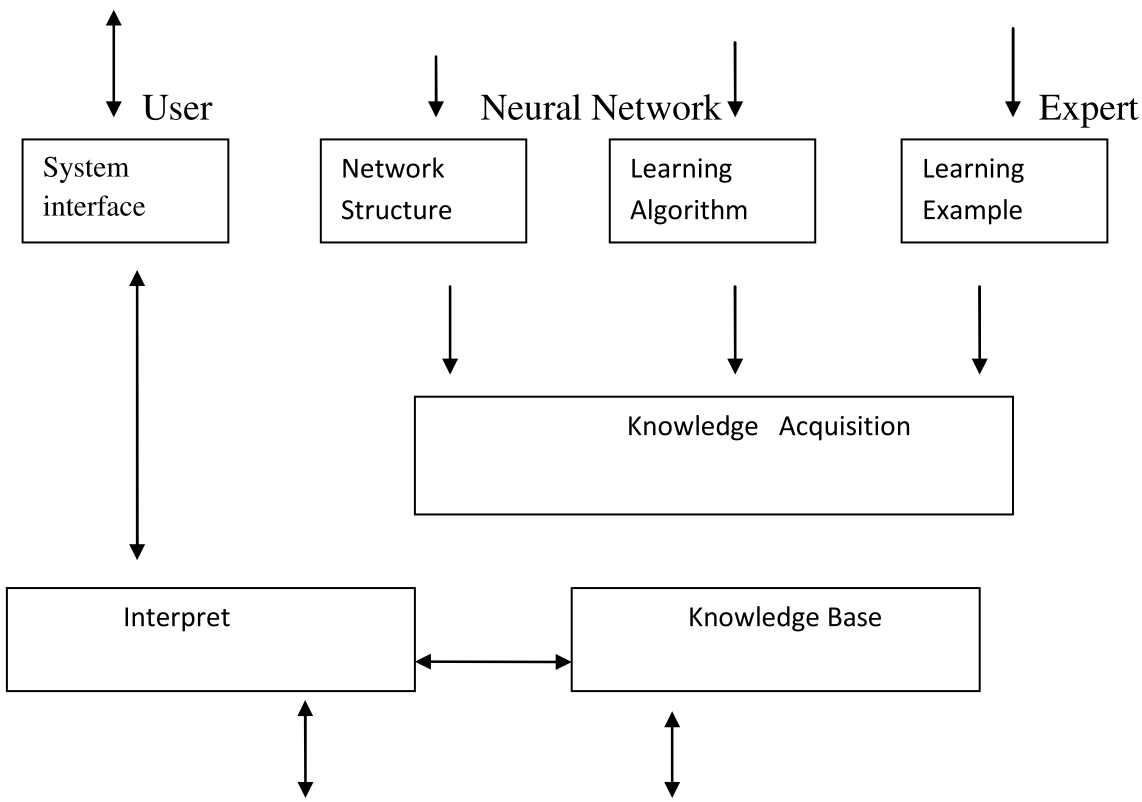

Fig 3: Basic structure of Neuro-Expert System

Selecting neural network architecture and calling learning algorithm of neural network can acquire knowledge for knowledge base. When a new learning instance is input, the knowledge acquisition module automatically gets new distribution of network weights to update the knowledge base by studying new instances.

3.4.1 Knowledge acquisition based on neural network

From the point view of fault diagnosis, knowledge is a complex of facts, concepts, rules, methods, technology and abilities. The field knowledge is obtained by the experts summarizing and concluding the practical experience in the long time of studying and handling problems in certain field The knowledge acquisition of neural network is to make the system output be as much as possible with the same answer given by experts in the same conditions of inputs, so that the network has similar capabilities to solve problems with the domain experts.

4. DESIGN AND IMPLEMENTATION

The proposed system was design to deal with faults in the engine and simulate diagnosis ideas of maintenance experts to find and remove automobile troubles. The system was designed to be secured with each category of users restricted to their own specific roles and be user friendly and efficient. Fig. 4 show the design flow process of implementation employed in this study

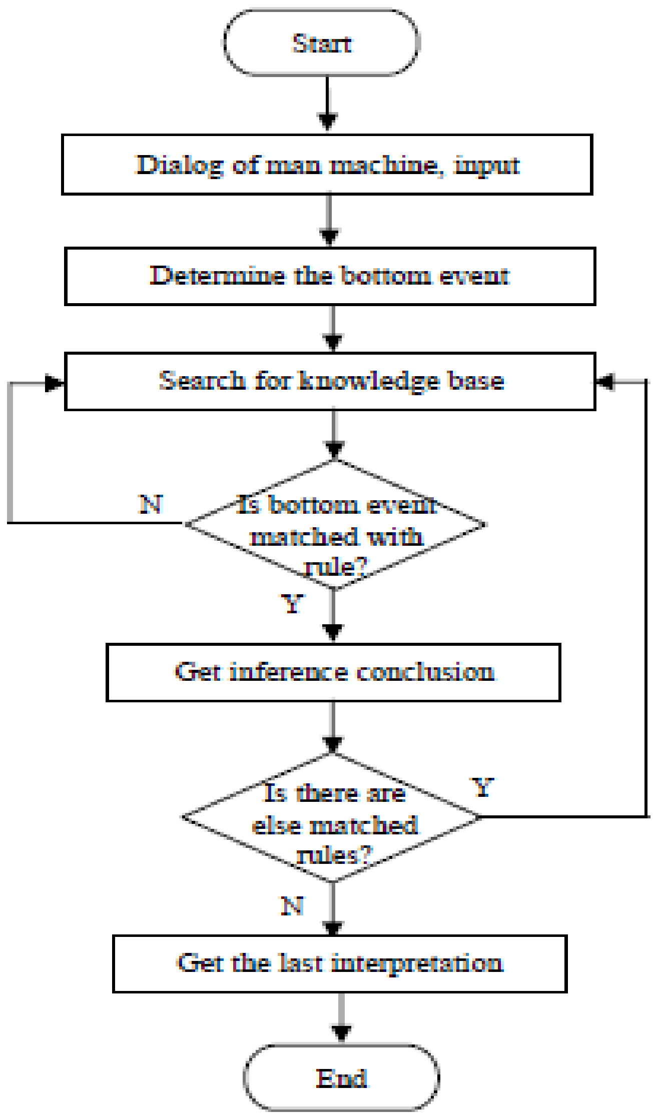

Fig. 4: The Design Methodology

However, this system classifies automobile failure into two major categories

1. Failure mode analysis of light {FMAL}
2. Failure mode analysis of engine abnormal sound {FMAS}

Fig. 5 shows the system welcome/login page on how a user can interact with the system.

Figure 5 The Welcome/Login page interface

The Fig. 6 platform is used to create an interactive section between the user and the application. The log in form only allows the user to input their name and it accommodates only strings data types. Then, next session pop up.
Fig. 6 showed the classification page faults that could be diagnosed.

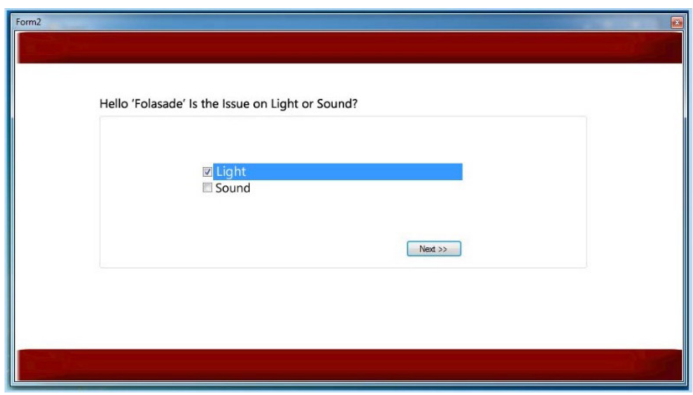

Fig. 6: The Classification Page

Failure Mode Analysis of Light: If the fault is about light then, the cause could be one of these three main reasons.

1. Check Engine Light {CEL}
2. Anti- Lock Brake System Warning Light {ABS}
3. Tire Pressure Monitoring System Warning Light

CHECK ENGINE LIGHT {CEL}: Indicate anything from a failed sensor to serious engine malfunction

FAULT 1 COIL ON PLUG

Functions: Provides the electric current for the plug to spark with ignites fuel.

Symptoms of failure includes

1. No start, hard start, low crank tune
2. Misfire, lack of power
3. Poor fuel economy

Fig. 7 show the symptoms of failure that could be encountered

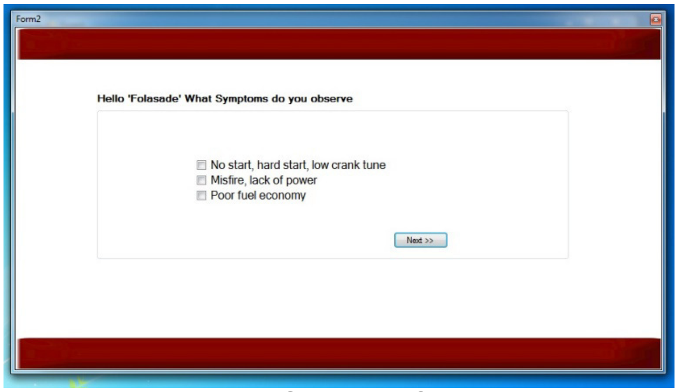

Fig. 7: The Symptoms Observed

FAULT 2 COIL

Functions: Provides the electrical current for the plug to spark which ignites fuel.

Symptoms of failure includes

1. No start, hard start, low crank tune
2. Misfire, lack of power
3. Poor fuel economy

FAULT 3 EXHAUST GAS RECIRCULATION VALVE

Functions: 'Gate' that allows exhaust gas back into engine resulting gas in a cooler, more complete burn of the fuels

Symptoms of failure includes

1. Poor engine performance
2. Failed emission test
3. Engine surging

FAULT 4 MANIFOLD ABSOLUTE PRESSURE CENSUS

Functions: Measures how hard engine is working for fuel adjustment.

Symptoms of failure includes

1. Lean or rich turning
2. Spark plug fouling
3. Premature engine bearing wear

FAULT 5 MASS AIR FLOW CENSOR {MAF}

Functions: Monitors the mass of air entering engine to balance the amount of fuel needed for engine demand.

Symptoms of failure includes

1. Poor fuel mileage (as vehicle does not mix the air and fuel property when the MAF is malfunctioning)
2. Poor performance due to weak acceleration, stalling and rough idling
3. Vehicle may not start.

FAULT 6 CRANK POSITION CENSOR

Functions: in fonts coil when to send spark to fire engine.

Symptoms of failure includes

1. No start, hard start
2. Long crank time, misfire
3. Premature engine bearing

FAULT 7 IGNITION CONTROL MODULE

Functions: Control amount of electrical current created by coil.

Symptoms of failure includes

1. No start hard start, long cracking start
2. Misfire, lack of power, poor fuel economy.
3. Spark plug fouling
4. Catalytic converter failure

FAULT 8 CAM CHAFT POSITION CENSOR

Functions: Informs coils when to send spark plug to fire engine.

Symptoms of failure includes

1. No start, hard start
2. Long crank time, misfire
3. Premature engine bearing

FAULT 9 OXYGEN CENSOR

Functions: Measures oxygen to notify computer to increase or to reduce fuel supply to engine

Symptoms of failure includes

1. Reduced gas mileage and engine performance, can cause damage to the catalytic converter
2. Failed emissions test

All the above SOF are further classify into eight symptoms

SYM 1: No start, hard start, long crank time, misfire, lack of power
SYM 2: Poor fuel economy
SYM 3: Poor performance
SYM 4: Premature engine bearing wear
SYM 5: Lean or rich running, spark plug fueling
SYM 6: Catalytic converter failure
SYM 7: Failed emission test with engine surging
SYM 8: Reduce gas mileage

ANTI- LOCK BRAKE SYSTEM WARNING LIGHT {ABS}: Means your ABS is compromised and could lead to brake system failure.

FAULT 1 ABS sensor
Function; sends sound to ABS computer to determine if the system needs to activate.
Symptoms of failure includes
1. ABS activate too soon, too late or not at all
2. Speedometer intermittent failure
3. Four-wheel drive inactive
4. Transmission shifts incorrectly

Other faults attached to brake are listed below

FAULTS
1. Damage fuse
2. Damage brake switch
3. Damage brake lamp
4. Damage test lamp
5. Short brake switch
6. Chick live line
7. Chick latter wiring

TIRE PRESSURE MONITORING SYSTEM WARNING LIGHT {TPMS}: Indicates that one or more tires are under inflated and could lead to a flat tire(s)

FAULT 1 TPMS SENSOR
Functions: Sends signal to indicate low tire pressure
Symptoms of failure include
1. Decrease tire life
2. Decrease fuel economy
3. Decrease brake ability
4. Decrease overall vehicle stability

Failure Mode Analysis of Engine Abnormal Sound: If the fault is about sound then the two major cause are;
1. Bearing
2. Knock sound

Bearing: there are different types of bearing which includes;
1. Compressor bearing
2. Roller bearing
3. Alternator bearing
4. Belt bearing
5. Water pump bearing
6. Power steering bearing

Knock sound: there are two major types of knock sound
1. Cam shaft
2. Crank shaft

However, some sound analysis will be listed for clarity. one probably know how one's vehicle sounds when it's running properly. Listening to one's car can help you troubleshoot problems. If you hear a strange sound, pay attention and react accordingly.

1. If a high-pitched squeal that stops when you shut off your engine is heard: Readjust or replace the belt. These belts should have about half an inch of play and shouldn't be frayed, cracked, or glazed on the underside.
2. If a continuous high-pitched sound that may continue after the engine's shut off is heard: Check the radiator pressure cap. The rubber gasket may be worn.
3. Something ticks rhythmically while the engine idles: Shut off the engine, wait ten minutes for the engine to cool and the oil to settle, and then check the oil level. If there is enough oil, have a mechanic check the valve adjustment.
4. If a loud tapping or knocking sound in the engine is heard, pull to the side of the road and call for road service. The source may be a loose rocker arm or carbon buildup inside the engine, but if it's a loose bearing or a faulty piston, it can destroy the engine.
Mild knocking or "pinging" may be the result of using fuel with the wrong octane rating.
5. If the engine running after ignition is turned: The engine is dieseling. This condition only happens to cars with carburetors. It is usually caused by an idle speed that's set too high or excessive carbon in the combustion chamber.
6. If a whistling noise coming from under the hood is heard: Check the hoses for vacuum leaks. If the whistling comes from inside the vehicle, there's probably a leak in the weather stripping.
7. The engine idles with an offbeat rhythm: It's probably misfiring. Turn the engine off and try the following:

- *Check the spark plug cables for breaks or shorts in the wiring.*
- *Remove the spark plugs one at a time and check to see if they're clean and properly gapped. Replace any that are fouled or burned.*

If attending to the spark plugs doesn't help, have a technician check the ignition system with an electronic engine analyzer.
8. The idling is rough but even: Have a technician check the compression in each cylinder.
9. If the car makes a loud, abnormal sound: A hole in the muffler is probably the cause. Replace it immediately.
10. The horn is stuck: If the horn gets stuck, pull the wires to stop the noise.
11. If a sound is heard but can't locate the source: Get an old stethoscope. Take off the rubber disc and insert a piece of tubing in its place (about 1-1/2 inches will do). Then put the plugs in your ears, run the engine, and move the tube end of the stethoscope around the hood area. The stethoscope amplifies the sound as you near the part that's causing it.
12. If whining or humming sounds is heard on curves: The wheel bearings may be wearing.
13. If tires make a weird, rhythmic sound when drivinge: Check inflation, tire wear, and wheel balancing.
14. If squealing is heard when the brake is stepped on: The brake pads is worn down too far. Get them replaced immediately.
If there is drum brakes, brake linings that are glazed or worn can cause them to squeal as well.
15. If rumbling noises is heard coming from under or toward the rear of the vehicle: The trouble could be a defective exhaust pipe, muffler, or catalytic converter; or it could be coming from a worn universal joint or some other part of the drive train. Have a service facility put the car up on a hoist and find the problem.
16. If clunking under the vehicle is heard, especially when one goes over a bump: Check the shock absorbers and suspension system. If the sound is toward the rear, tailpipe or muffler may be loose.

5. RESULT GENERATED

The inference engine is the processor in the expert system that matches the facts contained in the knowledge base to draw conclusion about the problem. If criteria are certified on checkbox click and next button click, it brings up an inference (If Knowledge Matches with Rule it gives the inference and conclusion). The fault in the car base on the user input is the coil on plug which is under failure mode analysis of light.

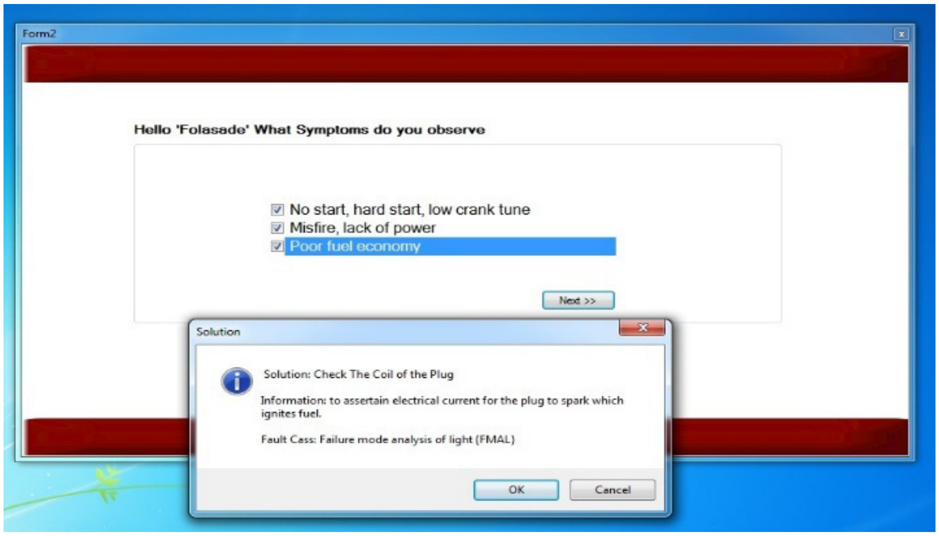

Fig. 8 Unsatisfactory Criteria

But for situation when the criteria are not satisfied the next set of question pops up as shown in Fig. 9

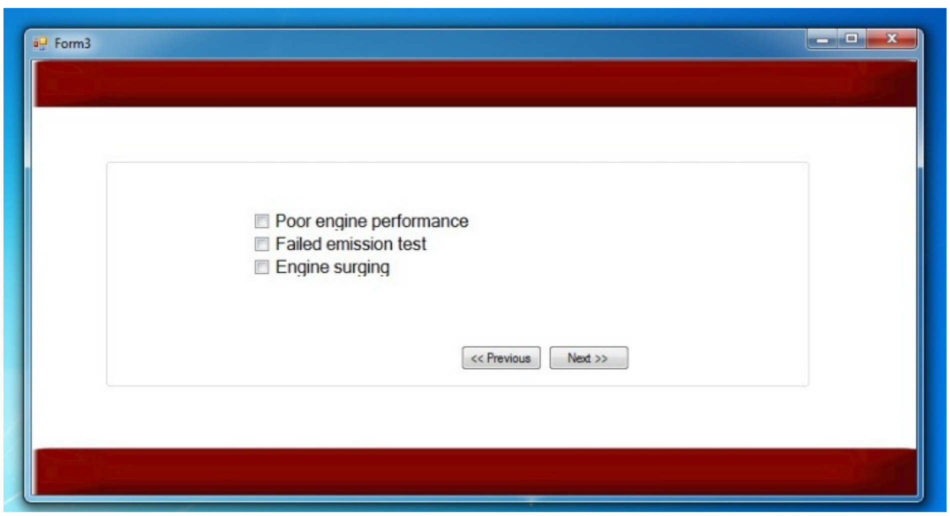

Fig. 9: Matching Rule

If Knowledge does not match with rules it goes to the next page to check if any rule matched the search) as shown in Fig. 9

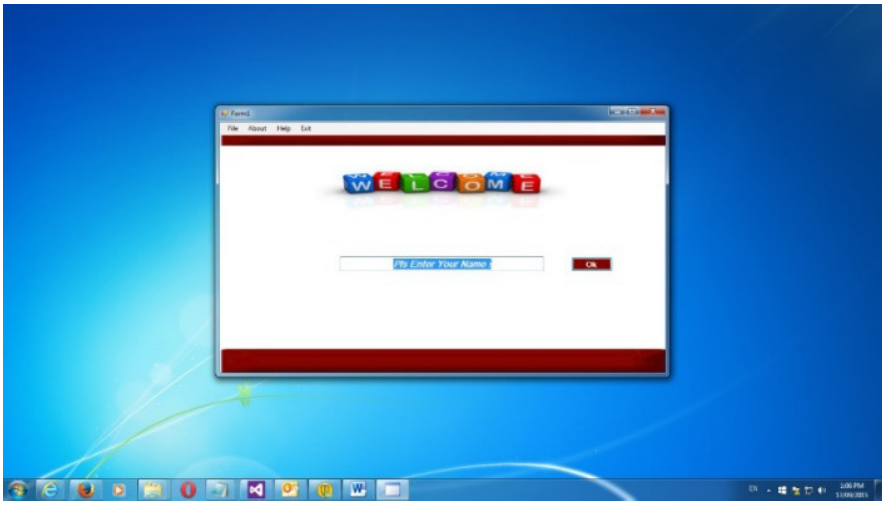

Fig 9 Home Page

If criteria are satisfied on OK button click, it returns back to the home page. (Returns back to the home page after success) as shown in Fig 9.

6. CONCLUSION

On the basis of analyzing the features of automobile fault diagnosis expert system based on neural network analysis, an experiment was carried out and realized by making the check engine light as example. The results showed that the proposed method automatically diagnose fault in automobile. The system has good fault tolerance, feasibility and stability and it has certain application value.

In the matter of failure modes of automobile, the system needs more expert knowledge to form a complete knowledge base. It should be continually improved in the latter practical application and finally the truly practical automobile fault diagnosis expert system can be achieved.

The system indicated that a full expert system will be practical and can be extremely useful in providing consistent automobile failure detection. Further work is needed to improve the system by adding sufficient domain knowledge that represents domain knowledge thoroughly.

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