To this figure, data type property is not used, as shown in Figure 2.2.

These classes are basic data model for borrowers' IB2PLAP lending. They represent knowledge of borrower's loan process. All borrowers' loan design was computed by these data model.

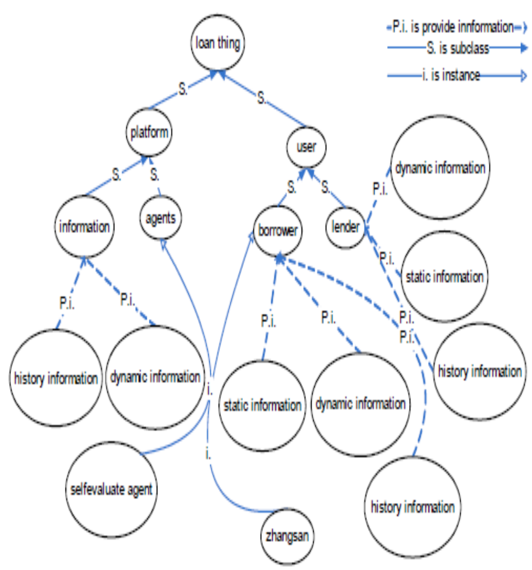

Fig. 2.2: Classes of ontology in IB2PLAP Lending (Xingsi and Zhengyi, 2017)

P2P Process Model

The P2P lending process is much simpler than bank loan process because the characteristics of P2P lending is much appeal to SME and personal borrowers, because they can provide little financial certificate and few mortgage assets. It should be noted that the credit analysis in P2P lending relies on users' information. So the credit method is different from bank.

Figure 2.3, shows that the application process in P2P lending obviously needed more information and operations compared with bank loan. The first reason is that P2P lending needs more information for credit audition. The second reason is that P2P lending allows lenders to choose a borrower, so the information flow is more complex than bank loan.

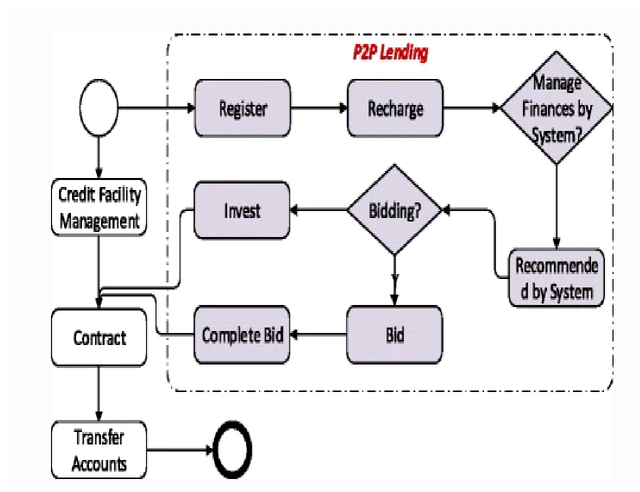

Fig. 2.3: Process Model on P2P Lending (Wang *et al.*, 2015).

Challenges of the Existing System

Some of the weaknesses of the existing system include:

i. The loan management is not very good in P2P lending, because it does not track the post-loan information on borrowers.

ii. Family members, Relative, Friends are considered first for allocation and payment.

iii. Increase in time taking for completion of transactions.

b. Analysis of the Proposed System

The proposed system is an intelligent model for loan allocation and payment using ontology algorithm. We adopt an Intelligent Bank – To- People(IB2P) with Simon framework model which uses a single transaction operation such that one lender(Microfinance Bank) with many borrowers(members, cooperatives) as reduce the complexity against the existing models. IB2P model consist of three (3) major modules; BORROWERS, PLATFORM, and LENDER. For borrowers to access loan from the microfinance bank (Lender), he/she will register with the platform where weekly monetary contributions are assessed for loan recommendation and disbursement. The intelligence system test conditions for loan approval using regular monetary contribution without skipping as a parameter for eligibility and recommendations. An automatic code generation is generated for borrowers who are eligible for loan payment so as to enhanced record tracking purposes for loan recovery. Our conceptual process model which is based on the well-known Simon framework (Simon, 1977) identifies four different phases—intelligence, design, choice, and review. We formulated the decision-making process model for borrower, which includes gathering information about the loan problem situation (intelligence), identifying various alternatives (i.e., formulating models) through which the problem can be solved (design), choosing the best alternative that meets the criteria (choice), and evaluating and revising the alternative (review). Figure 2.4 shows the architectural diagram of the proposed system.

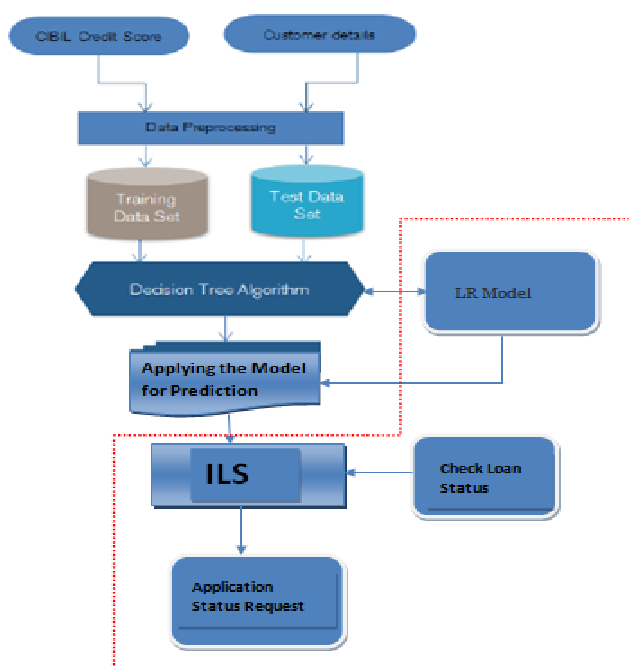

Fig. 2.4 Architectural Diagram of the Proposed System

Explanations of the Proposed System Architecture

Decision Tree (DT) Model

DT (Shown in Fig.2) is a supervised learning algorithm used to solve classification and regression problems too. Here, DT uses tree representation to solve the prediction problem, i.e., external node and leaf node in a tree represents attribute and class labels respectively. The pseudo code for DT model is depicted in the following section:

Step 1: Best attribute is chosen as the tree's root.

Step 2: Training set is divided into subsets, such that, each subset comprises similar value for an attribute.

Step 3: Step 1 and Step 2 are repeated for all subsets until all the leaf nodes are traversed in a tree.

LR Model

In general, linear Regression model was used to predict the functionalities of a continuous variable, say for example ―Y‖. If the variable ―Y‖ is categorical, instead of continuous, then the LR method is adopted. The output of LR model is dichotomous i.e., binary possibilities, used for prediction of loan sanction possibilities. Properties of LR include (1) dependent variable(s) follows Bernoulli distribution and (2) Maximum likelihood is used for estimation. Further, the function f(g) is a logistic function, referred as Sigmoidal function.

Members: Are individuals who registered with the cooperatives for easy accessibility to loan payment. Members can make their repayment through the leader or the platform by uploading proof of payment to the leader for updating.

Intelligent Loan System (ILS)

The intelligence agent contains information agent that obtain, aggregate, and assess relevant information from the borrower. All of the design, choice, and review agents may request information relating to their task from the Intelligence agent, if required. The design agent contains analyzing agent (A) and proposing agents (P). They are:

i. **Self-evaluation Agent (A):** It is used to analyze borrower's circumstance based on regular weekly monetary contributions without skipping (i.e. contribution regularities, rate etc.) and help borrower to identify his loan requirement. Self-evaluation Agent first assesses borrower's status by interacting with borrower or accesses entities. Then it proposes a list of loan suggestion.

ii.Goal Assessment Agent (A), It is used to help the borrower to define his loan goal. It reasons on borrower's profile and system's dynamic information. This agent also allows borrower to define his loan goals (other than those provided in the list) to the agent. In this way, borrower can customize loan rate, loan means and other information.

iii. **Risk Estimation Agent (A):** For each loan goal, the risk estimation agent evaluates the loan risk according to the borrower's related information which is credit, loan history and other available information. This agent tells the borrower get the loan probability.

iv. **Loan Template Agent (P):** For different kinds of utility-tolerance borrower, the loan template agent generates different loan templates by using fuzzy rules (Simon, 1977) for different loan profile models. Borrower can choose his favorite template as his portfolio and customize this template (i.e., adjust the loan rate, loan amount or loan period) with his own preferences.

v. **Loan Allocation Agent (P):** It is used to provide loan allocation recommendations to lender (microfinance bank) automatically.

There is only one Optimization Agent in the choice agent. It uses recommendation technology to get the score and list the designs by score descending at different types.

The outcome of the design and choice agents is an optimized loan solution, which contains a selection from a weighted loan combination that suits the borrower's objective and suggested allocations that maximize the expected return while accepting the degree of cost and risk the borrower can tolerant.

The Review group consists of two agents: cost evaluation agent and resolution agent. The first one is used to compute the loan cost and give advice to borrower; the last one is used to check the conflict between loan restrictions. If there is no contradiction between the interests of the Design and Choice Agent and the Review Agent, the investment optimization advice will be sent to the borrower, indicating that the entire process is complete. If there are contradictions, the Resolution Agent will take some initiatives to make a judgment and resolve the conflict and the system can adjust the borrower profile according to the borrower's selection.

LENDER: The lender module contains the Microfinance bank whose operation is to manage every transaction on the platform. Microfinance bank serve as an intermediary between the borrower and the core or primary financers like the federal government and other interested financers. They are all connected together with the platform. Monitoring the performance of the borrower can be done through the system.

c. Algorithms for the Proposed System

The algorithm for the loan allocation and repayment system is as specified below:

Step1: Create borrower's account

{(void createaccount(String Name_of_Borrower)}

Step2: Loan request by borrower

If (Contribution < Amount Requested)

{Status="NOT ELIGIBLE";

}

Step 3: **I**dentifying alternative courses of action. Considering all of the possible loan plans will help to make more effective and satisfying decisions.

Else if ($Contribution≥ Amount Requested)

{Status="ELIGIBLE";

}

Step 4: **V**aluating the alternatives, taking borrower's credit situation, individual values, and current economic conditions into consideration.

{Loan is approved and disbursed;

Step 5: Consists of creating and implementing a loan plan. This step requires choosing ways to achieve borrower's goals.

Else

{Status="NOT REGULAR and NOT ELIGIBLE";

}

Step 6: Stop

End if

3.0 Results and Discussions

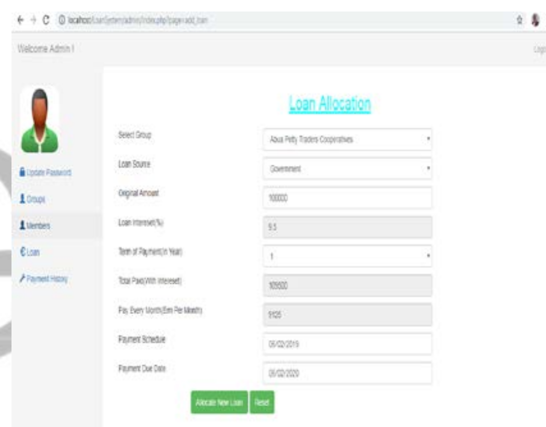

Fig. 3.1: User loan allocation interface of the system

X=SEX	Y = DEPOSIT
Male	2000
Male	10000
Male	2000
Female	2000
Female	2000
Male	2000
Female	2000
Male	2000
Male	2000
Male	2000
Female	2000
Male	2000
Female	10000
Male	2500

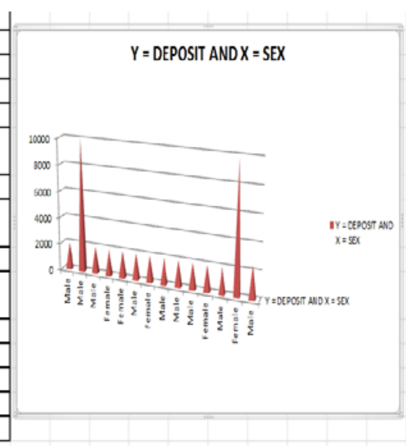

Fig. 3.2: Membership Deposit

In figure 3.2 we indicate Y as the deposit in a database; X is the sex. In figure 3.1 we plotted the value of x against y. It shows that one male and female has the highest deposit which is 10000. The software developed from our proposed model is shown in figure 3.1. Through experimentation with input data, outputs were generated on program running. From the experimental setup of the program interface shows individual/cooperative who are trying to borrow 50000 naira for 1 year and his monetary contribution in a month is 5,000 naira with an interest rate of 9.5%. After entering the input data then click on the "check eligibility" button, the system would evaluate his monthly contributions whether he is eligible or not using our ontology matching algorithm. The query result shows not eligible; therefore recommending maximum loan amount of 22809 naira for the borrower can request or apply for. The system also recommend the Equated Monthly Installation (EMI) of 2000 naira

4.0 Conclusion

This paper has adopted "An intelligent model for loan allocation and repayment system using ontology matching algorithm" borrowers to access loan from the government through microfinance bank (Lender), he/she will register with the platform where weekly monetary contributions are assessed for loan recommendation and disbursement. The intelligent system test conditions for loan approval using regular monetary contribution without skipping as a parameter for eligibility and recommendations. An automatic code generation for borrowers who are eligible for loan repayment, so as to enhance record tracking purposes for loan recovery. Our conceptual process model which is based on the well-known Simon framework, identifies four different phases intelligence, design, choice, and review, therefore conclusing that the model developed is recommended for banking sector in other to help the masses through the application developed.

5.0 References

Turrel, A., (2016). Agent-based models: understanding the economy from the bottom up.

Quarterly bulletin Q4: Bank of England.

Robert, I., and Bizer, C. (2013). Active learning of expressive linkage rules using genetic

Programming. Web Semantics: Science, Services and Agents on the World Wide Web.

Nanayakkara G. and Stewart J. (2015). Gender and other repayment determinants of micro financing in Indonesia and Sri Lanka. Int. J. Soc. Econ. 42(4):322-339.

Bachmann, A., Becker, A., Buerckner, D., Hilker, M., Kock, F., Lehmann, M., and Tiburtius, P. (2011). Online Peer-to-Peer Lending – A Literature Review. Journal of Internet Banking and Commerce, 16(2).

Galloway I. (2009). Peer-to-Peer Lending and Community Development Finance. Community Development Investment Center Working Paper. San Francisco: Federal Reserve Bank of San Francisco.

Freedman S., and Jin G. Z. (2008). Dynamic Learning and Selection: the Early Years of Prosper. com. com. working paper. College Park, MD.

Klafft M. (2008). Peer to Peer Lending: Auctioning Microcredits over the Internet. Proceedings of the Int'l Conference on Information Systems, Technology and Management.

Xingsi X. and Zhengyi T. (2017) "An Evolutionary Algorithm based Ontology Matching System" Journal of Information Hiding and Multimedia Signal Processing.