

# APPLYING MACHINE LEARNING TO THE SORTING OF RECYCLABLE CONTAINERS

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## ABSTRACT

The recycling of glass, steel, and plastic containers provides a means of drastically reducing the demand for raw materials in addition to extending landfill life spans. Past automation attempts have focused on bulk property separation techniques and have strived for complete removal of selected material types. Herein, the problem is addressed from a more marketable perspective whereby material removal efficiency is measured relative to decision accuracy and not solely on the amount of material diverted from the main waste stream. This project applies machine learning strategies to the task of material segregation using an induction algorithm (AIMS) to produce a dynamic knowledge base. This paper discusses the use of light transmission in the detection of glass clarity and the ability to separate glass, plastic, and metal containers using acoustic signatures. The overall goal of this work is to move machine learning technology from the laboratory into an on-line process control scenario, providing a foundation for "intelligent" automation.

## INTRODUCTION

The concept of automating the processing and disposal of solid waste is not a new one. Currently, there exist various types of machinery which attempt to sort one material from another with differing degrees of success. The key area of originality and the emphasis of this study is the coupling of artificial intelligence

(AI) algorithms with an array of material sensors to form an "intelligent" automation system with a dynamic knowledge base. Recent advances in the utilization of machine learning in the design and control of manufacturing systems in conjunction with the continuing decrease in the cost of computer control hardware promise to change the cost-to-benefit ratio currently attributed to processing streams of commingled recyclable containers. Collection and processing costs are significant when compared to the revenue received for a general municipal mix of containers. Communities typically wait until landfill or other waste disposal methods increase in cost so as to justify recycling. Intelligent automation could increase the revenue potential of recycling; therefore, providing necessary incentives for the establishment of waste reduction programs.

The goal of this project is to develop a knowledge processing system capable of recognizing unique feature patterns which can be used to segregate commingled waste streams containing glass, plastics, and metals into individual streams. It should be noted that separation efficiency may be assessed from two different perspectives. The first, and most obvious, is the amount of material classified by the system and removed from the primary waste stream. In statistical terms, this can be seen as minimizing Type I error, or the error resulting from incorrectly identifying an object and thereby failing to remove it from the primary stream. The second perspective addresses the accuracy of the classification and reflects the purity of the individual streams. This can be described as minimizing Type II

errors, those in which an object is removed from the main stream and placed in the wrong substream. This project will be primarily concerned with the latter. At this point in the development, however, both error types are considered equally. Later models will incorporate numerical techniques for minimizing Type II errors.

Intelligent automation is dependent on the existence of an inductive mechanism able to process data into concepts which are available for use by monitoring routines responsible for process control. This project uses the Adaptive and Interactive Modelling System (AIMS) to interpret sensor data streams and produce an efficient description of object characteristics which will define material separation strategies [1]. These investigations will facilitate selection of informative sensors for use in a prototype sorting system. Not only will the prototype address the challenges of real-time interaction between sensors with differing signatures, but it will provide information pertaining to the on-line performance of machine learned results relative to PC processing speeds.

## AI-BASED SORTING TECHNIQUES

The application of AI methods to the container sorting problem comes at an opportune time. Significant gains in cost efficiency can be obtained by automating the processing of source separated materials. Source separation refers to the segregation of materials into two or more groups at the waste generation site. Source separation of recyclable materials has matured to a point where it should have a stable future among municipal waste processing strategies. Fully mixed waste processing systems show that recovery of recyclable materials is generally less than 15% of the waste stream, while source separation systems now exceed 25% and are expected to steadily increase [2]. The specific area of interest in this project is machine learning in which little or no a priori knowledge is assumed available for the construction of knowledge bases. Such learning-based algorithms are more robust than their counterparts, which rely on hardwiring physical features into a control circuit. The machine learning induction algorithm is able to adapt to changing situations through integrating new conditions and findings with those it has already seen. One of the key advantages lies in the ability to combine seemingly unrelated sensor information into the decision making process. Over time, the inductive system performance can exceed that of an expert system that is constrained by the limits of its hard coded knowledge base.

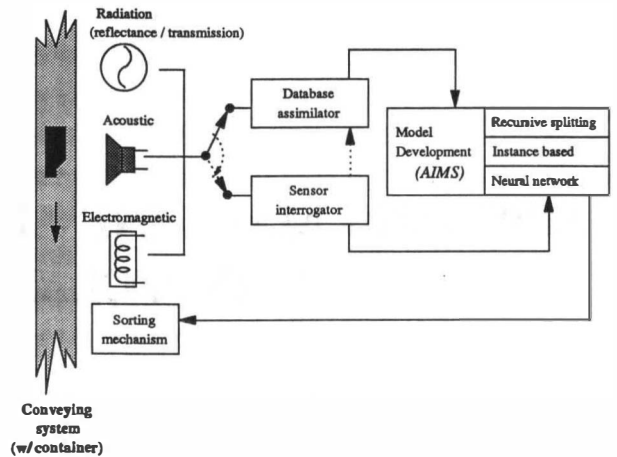


FIG. 1 SCHEMATIC OF COMMINGLED WASTE STREAM SEGREGATION SYSTEM

Figure 1 shows a conceptual overview of the prototype system, its components, and their interactions with one other. Both the database assimilator and the sensor interrogator will consist of PC-type computers with perhaps a single computer performing both tasks. The configuration shown illustrates the learning mode of the system. Training is done using a series of glass, plastic, and metal containers of various shapes, sizes, deformation patterns, and contamination levels. Each object is passed through an array of sensors and their respective responses are recorded. A combined database containing the accumulated sensor information for all of the containers will then be analyzed using AIMS. Comparison of several induction algorithms will be based on performance parameters specified by the user. Once the models have been derived, sensor output will be diverted to the interrogator for external assessment of the model's accuracy and completeness.

A machine learning algorithm learns how to perform a task based on a given set of examples (example driven) or through feedback from direct interaction with its environment (goal driven). This project focuses on example driven learning for which the user must provide a set of training examples. Examples are represented by a vector of input and output variables and the learning algorithm produces a model, or function, which maps the input to output variables. In our application, input variables are physical attributes of the container, such as size, color, optical density, and acoustic characteristics. Other input variables could be included to designate the object's origin and date of collection, both of which may be linked to the output. Herein, the output variables indicate to which class of container the example belongs.

Once a sufficient number of examples have been collected, the example driven learning algorithm is used to form a classification function. Decisions must be made as to the type of learning algorithm to be used and its associated control parameters which effect the desired predictive accuracy, execution speed, and formation time.

## INDUCTION ALGORITHM OVERVIEW AND SELECTION CRITERIA

AIMS is a robust and flexible system capable of both example and goal driven learning [3,4]. It can be considered a meta-learning algorithm because it can determine which learning algorithm and parameter settings are optimal for a particular problem. This is accomplished by using optimization (goal driven) to search a space of learning algorithms and find those that maximize one or more objective functions provided by the user. In the case of multiple objectives, AIMS produces a set of Pareto optimal models which are non-dominated with respect to all objectives. In other words, if a model is Pareto optimal, then there exists no other model which is better relative to all of the stated objectives. The advantage of using a set of Pareto optimal models for classification is that they provide greater flexibility and ideal behavior under a variety of circumstances. As an example, assume we give AIMS the objectives: maximize accuracy, minimize classification time, and minimize the number of input sensors queried. After the Pareto optimal models are obtained, perhaps a change may occur in the desired purity of the container streams. The user can then select a slower, but more accurate, model. Similarly, if the volume of material suddenly increases, a faster, but less accurate, model could be used and the conveyer speed increased. If an input sensor malfunctions, a model excluding that sensor could be used. Note that, although the requirements of the system may not be static, the given models still apply.

## RESULTS AND DISCUSSION

In this section, we present experimental evidence to support the claim that machine learning techniques can be effectively applied to container sorting. The results of two sorting tasks are reported herein. The first task was to classify bottles as clear or unclear based on the output of a single light sensor. The second task was to determine whether the container was glass, metal, or plastic based on the output of a single acoustic sensor. These results are based on single sensor inputs and

limited numbers of training examples; however, the results are extremely encouraging.

### Example Generation

The bottle sorting apparatus consisted of a chute through which bottles fell and were diverted into one of two streams at the bottom [5]. Each bottle passed between a solar cell and red LED, obstructing the light reaching the cell. This created a voltage fluctuation over time and yielded a waveform represented by a series of 150 samples of the voltage at 1 ms intervals. The 150 readings for each bottle comprised the input vector for that example. The output vector was a single number, 1 or 0, indicating whether the bottle was clear or unclear, respectively. A total of 679 examples were collected, 60% of which were clear. Therefore, the error of randomly guessing the class would be 50% and the error of a simple model which classifies everything as clear would be about 40%.

The examples for the material sorting problem were generated by impacting each container with a steel "bullet", recording the resulting sound waves, and performing a Fast Fourier Transform (FFT) on input signal. The sampling frequency was 128 Khz and consisted of 2048 data points collected over a 16 ms time period. The FFT computed the first 200 harmonics of the power spectrum using a bandwidth of 62.5 Hz. These values became the input vector for the object. Since there were three classes, the output vector was represented as three boolean numbers (o1, o2, o3) where a metal example was coded as (1, 0, 0), glass as (0, 1, 0), and plastic as (0, 0, 1). In total, 153 examples were collected, 58% of which were glass, 26% metal, and 16% plastic. The error associated with randomly guessing a type would be 33% and the error of a simple model which classifies all objects as glass would have been 42%.

### Comparison of Learning Algorithms

Based on past experience with AIMS, we have found three learning algorithms which may be effective for this type of learning problem. Such a task is considered difficult due to the large number of input variables, inherent noise in the measurements, and large number of examples to be processed. The selected algorithms were simple recursive splitting (SRS), neural network (NN), and instance based (IB). Briefly stated, SRS techniques recursively create binary splits perpendicular to scalar input feature dimensions which yield the largest reduction in predictive error. Resulting models are represented as decision trees. NN strategies assemble

highly interconnected simple computing elements mapping input to output parameters with weighting factors computed using back-propagation of error measures. Neural networks consist of nodes for each input feature which are linked to secondary or output nodes via weighted connections. IB learning techniques memorize the training set and make predictions by looking through it to find instances similar to the new point. The IB models created by AIMS contain the entire example set combined with an interpolation function for making predictions. The model looks for a given number of examples whose input features are the most similar to those of the prediction point and averages their output vectors to yield its prediction.

### Generating Pareto Optimal Models

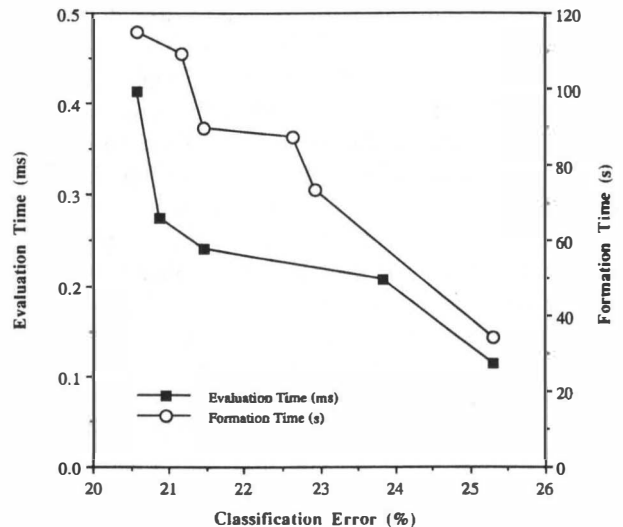
For the experiments herein, AIMS was given the objectives of predictive accuracy, model evaluation time, and model formulation time. Accuracy is reflected by the percentage of classification errors, evaluation time is measured in terms of milliseconds per classification, and formulation time is the number of seconds required to generate a specific model. To estimate the accuracy, 90% of the examples were used for forming the model and 10% were used for subsequent testing. The examples used for training were chosen at random, without replacement, and the remaining examples were used for testing. Since the accuracy of a learning algorithm will vary due to the random partitioning of the training and testing sets, we averaged the accuracy of the algorithm over 20 different training and testing sets and report both the mean accuracy and its standard deviation. The parameters of each learning algorithm were optimized by AIMS. Computations were done on a DECstation 5000 within a Common Lisp environment and each algorithm was allocated 10 hr for optimization.

Table 1 shows the characteristics of the most accurate models for both color and material sorting. For clear and unclear glass separation, recursive splitting performed the best relative to both accuracy and evaluation time. The instance based algorithm had a high accuracy, but was too slow to be practical. The task of sorting material types was best done using a neural network. It was, by far, the most accurate and had an acceptable model execution time. Investigation of the individual models revealed that the glass sorting problem could be accurately solved using approximately 10 of the 150 input features. This supports the SRS performance findings. Conversely, the material sorting problem did not lend itself to an abbreviated representation in that information was contained in a large

**TABLE 1 AIMS RESULTS FOR THE MOST ACCURATE MODELS FOR BOTH GLASS COLOR AND MATERIAL SORTING**

Experiment type	Learning algorithm	Classification error (%)		Evaluation time (ms)	Formulation time (s)
		Mean	Std. dev.		
Glass sorting	SRS	20.5	1.5	0.41	115
	NN	33.8	3.4	7.96	253
	IB <sup>1</sup>	22.9	1.6	9227	0
Material sort	SRS	32.7	2.7	0.43	198
	NN	7.3	1.6	8.67	88
	IB <sup>1</sup>	12.3	1.6	2046	0

<sup>1</sup> The instance based algorithm has no formulation time associated with it due to the fact that it contains a copy of the training set examples. However, the model execution time is extremely slow such that it is impractical for use in container sorting.



**FIG. 2 PARETO OPTIMAL MODELS FOR GLASS COLOR SORTING OBTAINED USING THE SRS LEARNING ALGORITHM**

number of the 200 input features. In such cases, a NN model is expected to perform better than one obtained using SRS.

Glass sorting results for the SRS and NN learning strategies are shown in Figs. 2 and 3, respectively. As noted on Table 1, execution times for the IB models are too large to be viable in this application. Both figures show the Pareto optimal models relating accuracy to evaluation and formulation times. Information from these figures is useful in many "what-if" scenarios. For example, Fig. 2 shows that to reduce decision errors from 25% to 21% requires that you use a model whose

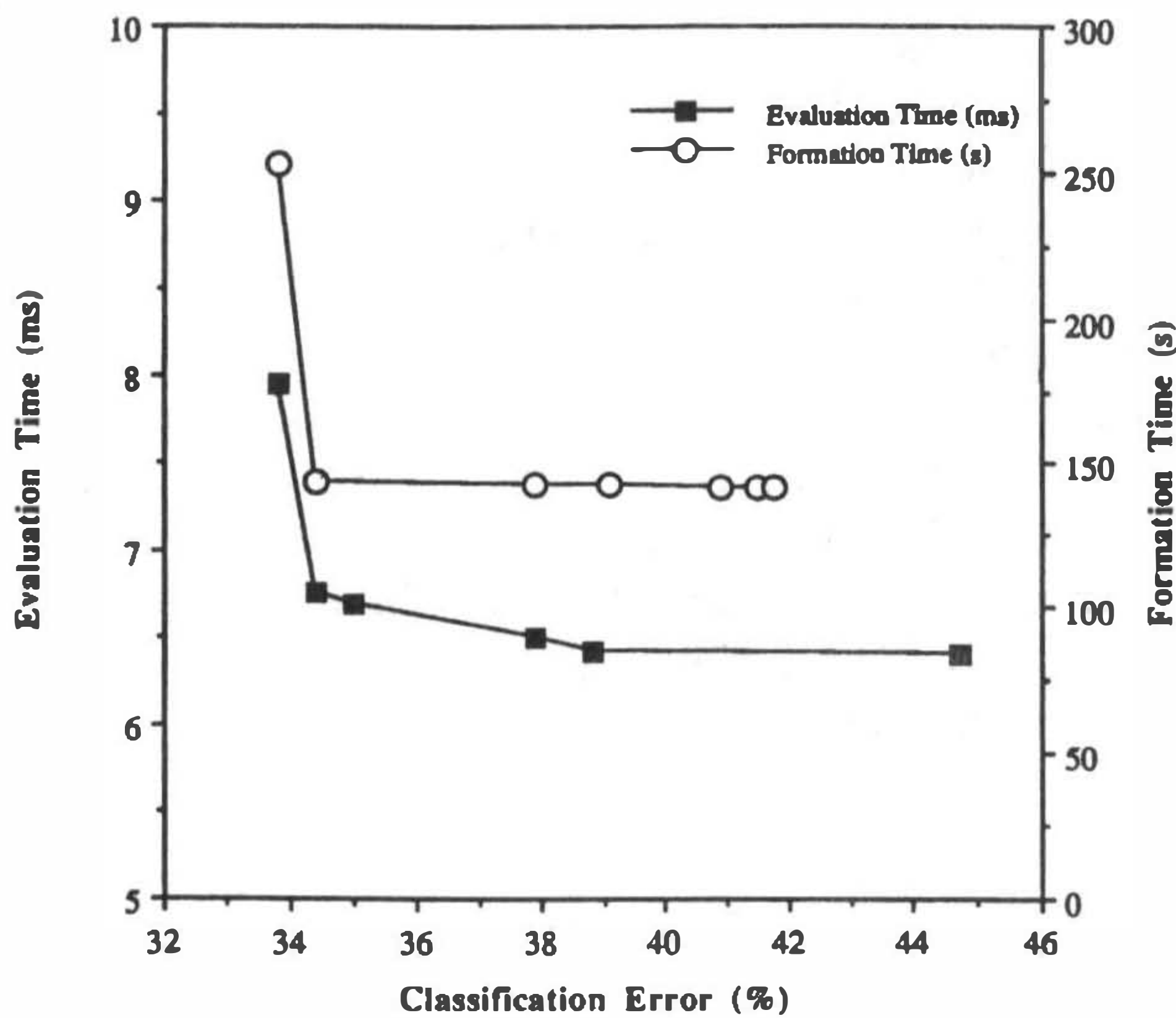


FIG. 3 PARETO OPTIMAL MODELS FOR GLASS COLOR SORTING RESULTS OBTAINED USING THE NN LEARNING ALGORITHM

evaluation time is roughly twice that of the current model. Also, in the event that models are being updated during system operation, the fact that the formulation time for the previous example increases by about a factor of three may be a constraint. Similar results were found for the material sorting problem.

### Effect of Manipulating Example Set Size

The above results indicate that machine learning achieves reasonable accuracy given a relatively small number of examples. Also of interest is the effect of increasing the number of examples on the resultant models. To answer this question, we varied the number of training examples and used prediction accuracy as the sole objective. The example set sizes for the glass sorting problem were 8, 16, 32, 64, 128, and 611. Similar set sizes for the material sorting problem were 16, 32, 64, and 138. The maximum number of training examples for both problems represented 90% of the respective data sets and, therefore, the associated models were those discussed in the previous section. Model accuracy was averaged, again, over 20 different training and testing sets with the number of testing examples being fixed at 25. The allocated model formulation and optimization times were increased in proportion to the number of examples. For every 16 examples in the training set, 1 hr of optimization time was allowed.

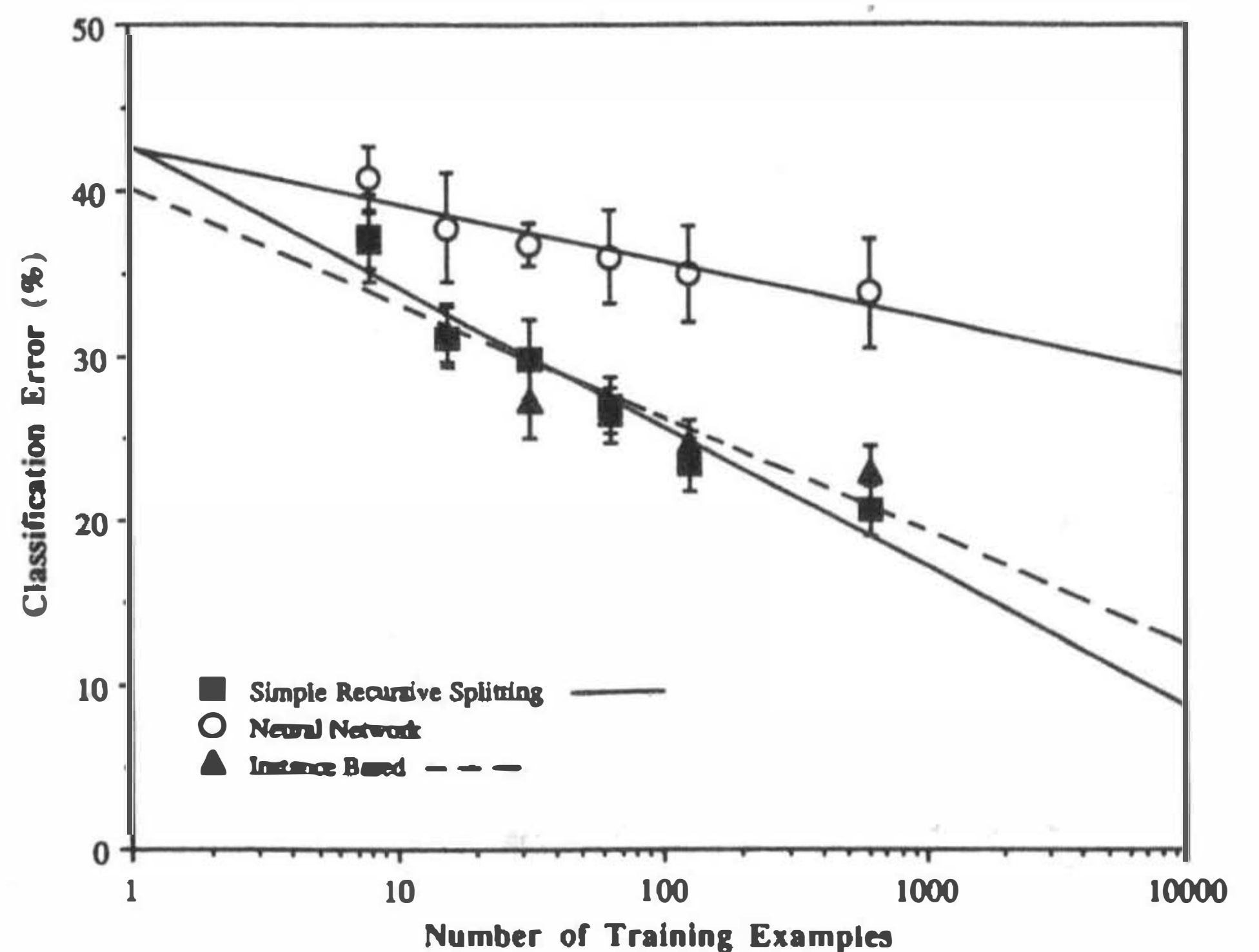


FIG. 4 COMPARISON BETWEEN THE NUMBER OF TRAINING EXAMPLES AND CLASSIFICATION ERROR

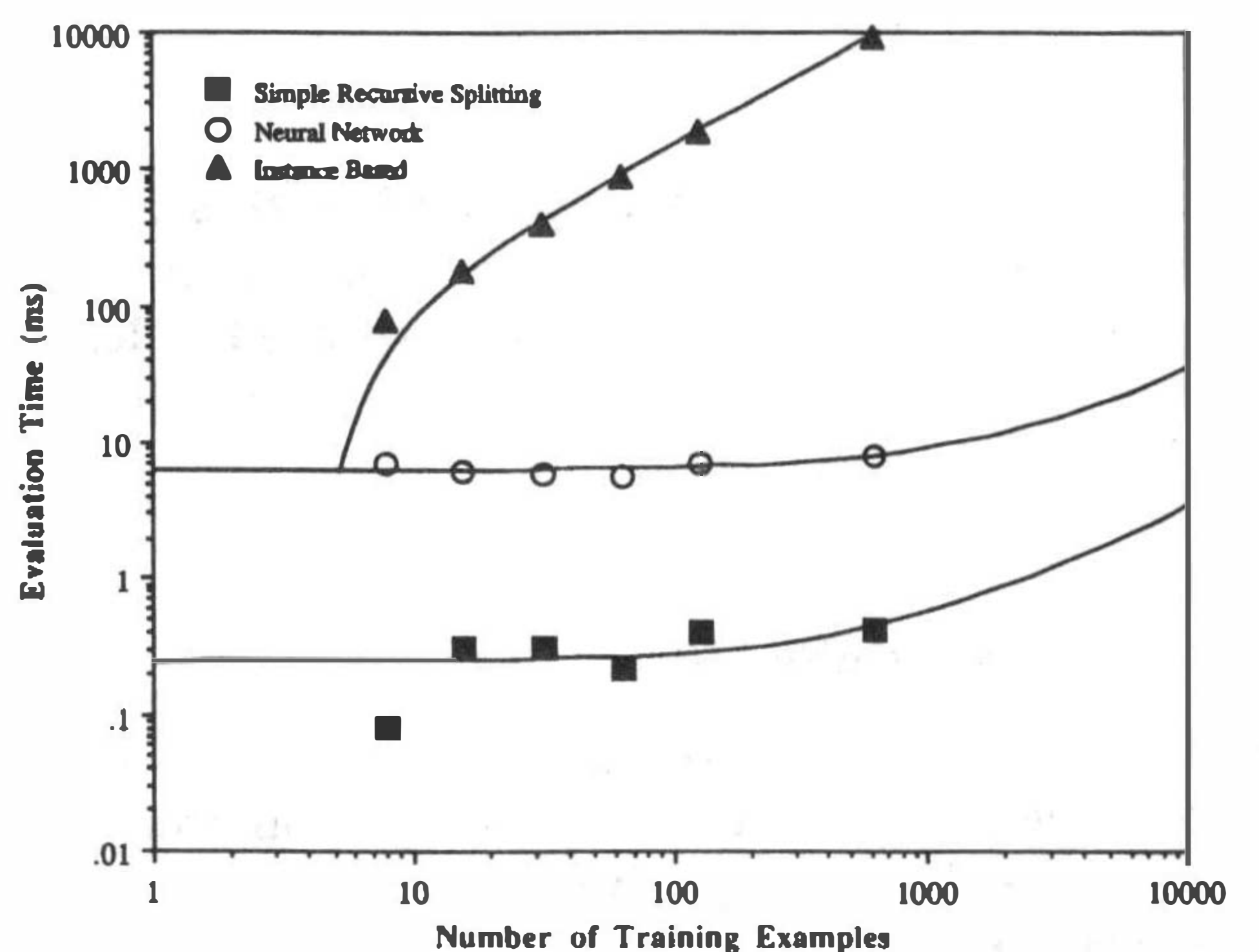


FIG. 5 COMPARISON BETWEEN THE NUMBER OF TRAINING EXAMPLES AND MODEL EVALUATION TIME

Figures 4–6 show how the various algorithms are effected as the number of examples increases. Each learning curve was fitted with a log or linear regression line resulting in  $R^2$  values between 0.54 and 0.99. These lines are not intended for use in computing exact values, but are shown to indicate trends in the data. Note that Fig. 4 shows that both the SRS and IB results yield similar reductions in classification error as the number of examples increases. However, evaluation times (Fig. 5) are drastically different with the SRS models being roughly 1000 times faster. Extrapolating from these learning curves indicates that using AIMS on more examples will yield more accurate solutions, as ex-

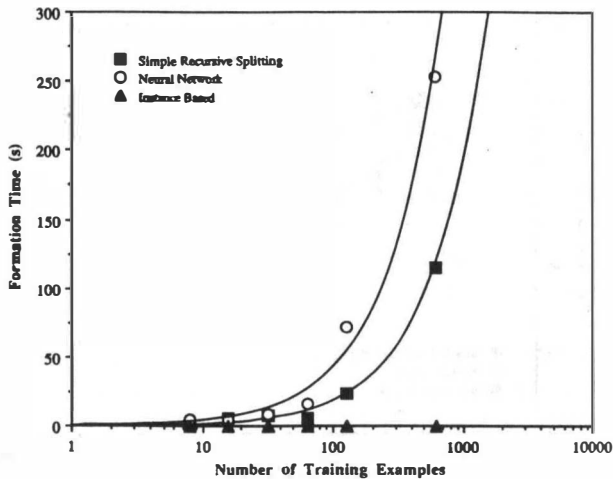


FIG. 6 COMPARISON BETWEEN THE NUMBER OF TRAINING EXAMPLES AND MODEL FORMULATION TIME

pected, while still producing models with acceptable execution speeds and formation times when implemented on a workstation or a comparable PC. Results from the material sorting problem reveal the same trends as discussed above.

## ONGOING RESEARCH

An ongoing aspect of this project is to keep abreast of developments in sensor technology, both from commercial and research perspectives. This permits the exploitation of currently available sensors which are economically feasible for inclusion into the sensing array as well as preventing duplication of efforts. Currently, enhancements are being made to both the color and acoustic sensors.

Comparisons and past experiences using light reflection and transmission characteristics of various objects tends to favor detection of transmitted energy for this application. Placing the object between the light source and the sensor will allow the sensor to ignore object contamination, such as internal debris or labels, while still allowing it to sense transmitted energy, given a minimal unobstructed region on the object. The color sensor discussed herein could distinguish glass clarity relative to a single color band, namely red. Hence, it was unable to discern specific bottle colors, only their brightness or shade. Initial investigations into the use of three filtered photodiodes spanning red, green, and blue wavelengths show great promise in their ability to collectively sort colors as well as shades. The new

configuration will also be less sensitive to temperature variations and infrared noise.

Studies have also been conducted to determine an appropriate mechanical method to induce vibrations into objects as they pass the acoustic sensing area. As a result, a configuration employing a rotating length of small link chain has been found to impact containers of all types without breakage or deformation while yielding signals of consistent strength for reliable measurement. Additionally, the use of inductive and capacitive sensors to distinguish aluminum, steel, and bimetallic objects is being explored.

## SUMMARY AND CONCLUSIONS

The application of intelligent automation in the processing of source separated waste streams is both feasible and timely. Control systems derived from knowledge extracted using machine learning induction algorithms address the problems of system adaptability and utilization of unrelated sensor types. Preliminary results from both light transmission and acoustic tests reveal the potential to distinguish clear and unclear glass as well as to segregate glass, metal, and plastic objects using emitted sound waves. Electromagnetic sensing will also be incorporated, but at present, specific sensors have not been selected or designed.

Using the AIMS induction algorithms, it was shown that recursive splitting techniques show promise and will be compared with results from neural network representations in an attempt to maximize processing efficiency. Instance based algorithms, although potentially accurate, are not feasible with respect to their evaluation times. System optimization parameters are classification accuracy and prediction frequency, with accuracy being the higher priority item. Although not incorporated in the preliminary models, weighting factors will be used in later efforts to account for the minimizing of Type II over Type I errors. This approach will yield sorted material groups that require no secondary manual sorting.

This project uses AI-based tools and techniques to create a decision making and quality control system for product classification and sorting. Such a system is not constrained by the scope of this specific project, but could easily be expanded to operate in numerous other classification environments. An application-oriented approach to on-line processing may be to use AIMS to determine the most appropriate learning algorithm for a specific problem and then produce a control system implementing a single learning strategy. This would facilitate the transporting of such strategies as recursive

splitting and neural networks to smaller computing platforms as both algorithms require little computer coding.

## ACKNOWLEDGEMENTS

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