**EXISITNG SYSTEM:**

SVMs are a class of supervised learning models that have been widely used for classification and regression SVMs are based on statistical learning theory and are better able to avoid local optima than other classification algorithms. An SVM is a kernel-based learning algorithm that seeks the optimal hyper plane. The kernel learning process maps the input patterns into a higher-dimensional feature space in which linear separation is feasible. The existing kernel functions can be classified as either local or global kernel functions. Local kernel functions have a good learning ability but do not have good generalization ability. By contrast, global kernel functions have good generalization ability but a poor learning ability. For example, the radial kernel function is known to be a local function, whereas the polynomial kernel function is a global kernel function. The main challenge lies in determining which kernel function should be used for the current problem instance or the current decision point. This is because the kernel selection process strongly depends on the distribution of the input vectors and the relationship between the input vector and the output vector (predicted variables). However, the feature space distribution is not known in advance and may change during the course of the solution process, especially in big data cyber security. Consequently, different kernel functions may work well for different instances or in different stages of the solution process and kernel selection may thus have a crucial impact on SVM performance. To address this issue, in this work, we use multiple kernel functions to improve the accuracy of our algorithm and avoid the shortcomings of using a single kernel function.

**PROPOSED SYSTEM:**

The proposed hyper-heuristic framework for configuration selection is shown in Figure 2. It has two levels: the high- level strategy and the low-level heuristics. The high-level strategy operates on the heuristic space instead of the solution space. In each iteration, the high-level strategy selects a heuristic from the existing pool of low-level heuristics, applies it to the current solution to produce a new solution and then decides whether to accept the new solution. The low level heuristics constitute a set of problem-specific heuristics that operate directly on the solution space of a given problem. To address the bi-objective optimization problem, we propose a population-based hyper-heuristic framework that operates on a population of solutions and uses an archive to save the non-dominated solutions. The proposed framework combines the strengths of decomposition- and Pareto (dominance) - based approaches to effectively approximate the Pareto set of SVM configurations. Our idea is to combine the diversity ability of the decomposition approach with the convergence power of the dominance approach. The decomposition approach operates on the population of solutions, whereas the dominance approach uses the archive. The hyper heuristic framework generates a new population of solutions using the old population, the archive, or both the old population and the archive. This allows the search to achieve a proper balance between convergence and diversity. It should be noted that seeking good convergence involves minimizing the distances between the solutions and PF, whereas seeking high diversity involves maximizing the distribution of the solutions along PF. The main components of the proposed hyper-heuristic framework are discussed in the following subsections.