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A Hyper-Solution SVM Classification Framework: Application To On-Line Aircraft Structural Health Monitoring

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Abstract

Support Vector Machines (SVMs) classification learning is a powerful paradigm to investigate inverse input-output relationship of a specific problem according to some available and representative dataset. In particular, SVMs are able to identify even non-linear relationship by mapping non-linearly separable data into potentially linearly separable one through families of spatial transformation (*kernel trick*). With respect to this, several parameters (i.e., kernel function and its internal parameters) have to be tuned; however the optimal configuration is usually difficult to be defined *a-priori*.

In this paper, a hyper-solution framework for SVM classification is presented. The main idea is to perform, simultaneously, three different SVM-based classification learning tasks: *Model Selection*, *Multiple Kernel Learning* and *Ensemble Learning*. The meta-heuristic known as Genetic Algorithms (GA) has been proposed to search for the most reliable final *hyper-classifier* (an SVM with a basic kernel, an SVM with a combination of kernel, or an ensemble of different SVMs, respectively), and the corresponding optimal configuration.

We have applied the proposed framework on a critical and quite complex problem: the on-line assessment of structural health of aircraft fuselage panels, a crucial task both in military and civilian settings. In particular, the framework has been used to implement a diagnosis task, that is detecting a possible damage and identifying the structural component involved, according to the strain field measured through a monitoring sensor network deployed on the helicopter fuselage panels.

Finite Elements (FE) simulation has been configured to simulate the response of a real panel to different damages. The resulting simulated strain fields have been used to build a dataset. Results obtained through 3 folds-cross validation proved the framework is reliable. Finally, when compared to results obtained by the authors in a previous work based on Artificial Neural Networks (ANN) classification learning paradigm, the proposed SVM framework proved to be more effective and reliable.

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1. Introduction

Research in classification learning may be mainly divided in two different and alternative streams: searching for the optimal tuning of the internal parameters of a single classifier (Model Selection) or defining the optimal combination of a set of basic (trained) classifiers (Ensemble Learning) (Rokach, 2009) through a suitable strategy (e.g., Simple or Weighted Voting System (Valentini & Masulli, 2002)).

Specifically for kernel-based learning strategy, such as Support Vector Machines (SVM) classification, another task may be performed, consisting in identifying the optimal combination of different basic kernels (typically linear combination). Although it can be thought as a Model Selection task, it is usually approached as a specific research stream known as Multiple Kernel Learning (Sonnenburg et al., 2006).

Looking at the overall classification learning process and the correspondent goal of identifying the most reliable classifier for a specific decision problem or dataset, it is usually complex (or even impossible) to define a-priori the most effective strategy as well as the most appropriate configuration of its internal parameter values: it usually requires to build and test a grid of different alternative configurations (“grid-approach”). Approaching all the three tasks contemporary (i.e., Model Selection, Multiple Kernel Learning and Ensemble Learning) in a unique framework by using a grid-approach requires a heavily time consuming learning process, increasing computational needs while enlarging the grid of possible configurations.

Search meta-heuristics are effective and efficient techniques able to take into account only potentially good configurations within a predefined grid, by using two mechanisms usually known as *exploitation* and *exploration*. The framework proposed in this paper is based on Genetic Algorithms (GA), initially introduced by Holland (1975), with the aim to unify Model Selection, Multiple Kernel and Ensemble Learning in a single high-level SVM classification learning framework.

This framework has been recently proposed by one of the authors and applied both on benchmark and real world dataset, providing interesting and encouraging results (Candelieri, 2011). In particular, with respect to real world problems, the framework has been already proposed in order to implement a specific decision support functionality in the healthcare domain, that is the early detection of destabilizations in chronic heart failure patients according to vital parameter values acquired at home (Candelieri & Conforti, 2010).

In this paper the authors investigate the benefit of the proposed SVM classification framework when applied to a critical issue in the aircraft structural health monitoring, that is the detection of possible damage on the fuselage of helicopter and the identification of the component involved, according to strain measurements acquired through a network of sensors deployed on the fuselage.

With respect to the aircraft structure maintenance while the direct relation can be effectively computed using Finite Element Method (FEM), (Katsikeros & Labeas, 2009; Zienkiewicz, Taylor & Zhu, 2005), the inverse relation required by on-line structural diagnosis and prognosis goals, remains difficult to be characterized but in really simple cases.

According to the ICT advances in the development of new sensors, the application of Machine Learning strategies to define a possible reliable relationship linking strain field to specific characteristics of a damage has recently gained new interest.

Artificial Neural Network (ANN) learning is commonly adopted to address most of the issues related to the aircraft structural health monitoring. In particular ANN-based strategies have been proposed to estimate damage features as well as remaining useful life of structural components (Sbarufatti et al. 2011a,b, Guez and Ahmad, 1988; Hoole, 1993). In (Trivailo et al., 2006) a survey on the application of ANN on structural health assessment in helicopters can be found. With respect to the ANN learning paradigm, the authors of this paper have also presented an approach based on hierarchies of ANN to provide decision support in structural health assessment (Candelieri et al, 2013 in press), in particular: diagnosis – consisting of *i*) detecting a possible damage, *ii*)

identifying the affected component and *iii*) estimating the damage centre and size – and prognosis – estimation of the remaining useful life according to the estimation of damage propagation.

In this paper, the proposed Support Vector Machines (SVM) classification framework is investigated in order to provide a most reliable diagnosis (i.e., detection of a possible damage and identification of damaged component). SVM learning has been already proposed for solving this task, even if not within a “wide classification framework” (Worden & Lane, 2001; Worden & Mason, 2007).

The rest of the paper is organized as follows: section 2 provides the reader with the description of data preparation and pre-processing and the required backgrounds about Genetic Algorithms and SVM classification; section 3 describes the algorithmic architecture; section 4 reports the experimental results comparing them with those obtained in their previous work (Candelieri et al., 2013 in press). Finally, conclusions and planned future works are reported.

2. Material and Methods

2.1. Dataset Generation via Finite Element Simulation

Software for FE simulation is the most efficient solution to generate wide datasets of damage-strain examples, avoiding the prohibitive costs required to acquire this data by performing damage on real world fuselage components. In particular, the FE simulation software used in this study (Katsikeros and Labeas, 2009) has been developed by one of the partners of HECTOR (Helicopter fuselage Crack monitoring and prognosis through on-board sensor network), a project co-founded by the European Defense Agency (EDA). Some parameters of the FE simulation have to be tuned in order to model a specific type of panel and a specific damage (i.e., material of the panel, tensions applied, damage centre and size); as result, the software provides the strain field.

The basic element of an helicopter fuselage is called panel, and it consists of two different type of components: bays and stringers. A stringer is a metal component, similar to an “L”, fixed to panel by several rivets, while a bay is a sheet between two stringers. Each panel consists of 3 bays and 4 stringers and its overall size is 50x60 cm (Fig.1).

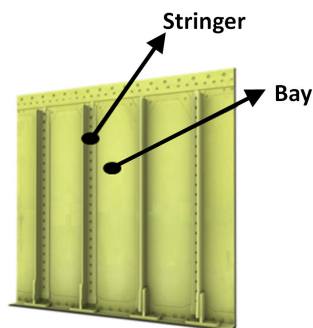


Fig.1 – A real panel of an helicopter fuselage: stringers and bays are indicated

Dataset was built by setting 7 different vertical lines of sensors in the FE simulation software: 3 on bays and 4 on the correspondent stringers. On each vertical line, strains are measured at 201 equidistant points, therefore $7 \times 201 = 1407$ overall strain measurements on each panel have been considered.

The FE simulation has been performed by taking into account, as reference structure, an aluminum panel and placing damages both on bays or stringers. Each simulation result consists of 1407 strain values, related to 201 ideal rows and 7 columns on the panel (3 columns are for bays and 4 are for stringers). Different damages have been simulated, separately for bays and stringers, by selecting center and size of each damage with a uniform probability distribution in order to make each simulation independent to another (*i.i.d.* samples). Moreover, one simulation with no damage has been performed.

According to technical requirements defined in the HECTOR project, a network consisting of 20 sensors has been deployed on a panel, having 4 ideal columns (stringers) and 5 ideal row. With respect to the different setting provided by the FE simulation software, a pre-processing step was needed to create a mapping between the positions of the real-world sensors network and simulated strain field.

A second pre-processing step has regarded data normalization: all tension values k_i were transformed as follows

$$k_i = \frac{k_i}{\frac{\sum_{i=1}^M k_i}{M}} \quad \forall k_i \in K$$

where k_i is the i -th strain value and M is the overall number of strain measurements. As reported in similar works (Katsikeros and Labeas, 2009 and Sbarufatti et al, 2011a,b), the normalization step is needed to remove the effect of the load and compare strain fields with respect to the damage and not to the load applied. The two pre-processing steps have to be performed anytime sensors network is reconfigured.

The following Table 1 summarizes the most important information about the dataset.

Table 1 – A description of the FE simulation dataset. Every instance is defined by a set of features representing strain values at the monitoring points.

Type	Number	Further Available Information
No damage	1	This instance is duplicated by adding Gaussian noise (5%) in order to obtain a comparable number of instances with respect to the other class (damage on bay and damage on stringer)
Damage on bay	3570	- Coordinates (x and y) of the damage centre; - Damage size (mm);
Damage on stringer	8098	- Coordinates (x and y) of the damage centre; - Damage size (mm);

2.2. Genetic Algorithm

Genetic Algorithm (GA) is a meta-heuristics based on the emulation the natural evolution process (Holland, 1975): as the most “fit” individuals have high probability to transfer their features to the next generation (*offspring*), so the most “good” solutions have more chances to “generate” new good ones, hopefully the best one (optimum) after several generations.

In recent years, meta-heuristics techniques have been proposed for SVM-related *Model Selection* (Huang & Wuang, 2006; Lessmann et al., 2006) and *Multiple Kernel Learning* tasks (Dioşan, 2008). Moreover, according to the benefits provided by *Ensemble Learning* in reducing the risk of error on predictions (Diettrich, 2000; Condorcet, 1785; Valentini & Masulli, 2002), as also reported by Condorcet in his work “*Essai sur l’application*

de l'analyse a la probabilité des decisions rendues a la pluralité des voix" (1785), GA has been proposed also for this specific learning task (He et al., 2006).

In GA, each solution is usually named *chromosome* and is defined by a string of values (*genes*). The generation of a new individual (solution) is performed by selecting two ones in the current population with a probability increasing with *fitness* (performance of the solution). A *crossing-over* operator usually produces two new solutions while a random *mutation* is performed on some of their genes (according to a predefined probability distribution). Selection and crossing over are usually identified as exploitation mechanism while mutation as exploration. Size of population, selection strategy, crossing-over, mutation and termination criteria regulate meta-heuristic search behavior and performances.

2.3. Support Vector Machines Classification

Support Vector Machines (SVMs) were originally proposed by Vapnik (1998). The basic idea consists in searching for a hyper-plane to optimally separate instances belonging to different classes and, contemporary, maximizing the distance of the instances from the hyper-plane. The optimal separating hyper-plane is expressed as a function of its closest instances (laying on the margin), usually named Support Vectors.

This definition represents the first formulation of the SVM classification learning task, usually known as *hard margin SVM*.

Given a dataset D of n instances, it can be represented as:

$$D = \{(x_i, y_i) \mid x_i \in \mathfrak{R}^p, y_i \in \{-1, 1\}\} \text{ with } i = 1, \dots, n$$

where y_i indicates the class to which the correspondent point x_i belongs, and p is the number of features describing the vectors x . Any hyper-plane can be expressed in following form:

$$w \cdot x - b = 0$$

that is the dot product between the normal vector (w) to the hyper-plane and a vector x . In order to separate linearly separable data, two hyper-planes can be identified. The correspondent region between them, where no data points are, is usually known as margin. The two hyper-planes are usually defined as:

$$w \cdot x - b = 1$$

and

$$w \cdot x - b = -1$$

with $2/\|w\|$ the size of the margin (i.e., distance between the two hyper-planes).

In order to avoid data points falling within the margin, the following constraint has to be defined:

$$y_i (w \cdot x_i - b) \geq 1 \quad i = 1, \dots, n$$

Therefore, the hard margin formulation consists in minimizing $\frac{1}{2} \|w\|^2$ subject to the previous constraint.

In Fig.2 an example of SVM classification for linearly separable data is presented.

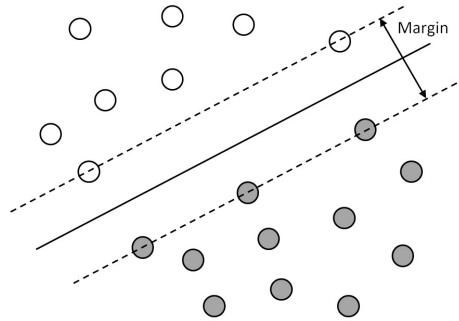


Fig.2 – An example of linear separation through margin maximization

However, hard margin SVM is effective only when data is linearly separable, a situation quite rare in real world problem. Respect to this, a second formulation, usually known as *soft margin SVM* has been proposed: it relaxes separation constraints in order to admit some classification errors which are limited through a penalization term in the objective function. A specific implementation of the soft margin formulation is named *C-SVM classification*, with C a regularization parameter for handling the trade-off between minimization of classification error and maximization of margin.

In order to permit an error classification, the constraint has to be modified as follows:

$$y_i(w \cdot x_i - b) \geq 1 - \xi_i \quad i = 1, \dots, n \quad \text{and} \quad \xi_i \geq 0$$

while the objective function becomes:

$$\min_{w, \xi, b} \left\{ \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i \right\}$$

Nevertheless, both hard and soft margin works with a linear hyper-plane, a really tight precondition in real world classification learning problems. Respect to this, the *kernel trick* has been proposed consisting in performing - implicitly - a mapping of the instances from the original space (*Input Space*) in a new one (*Feature Space*) in which they could be hopefully linearly separated.

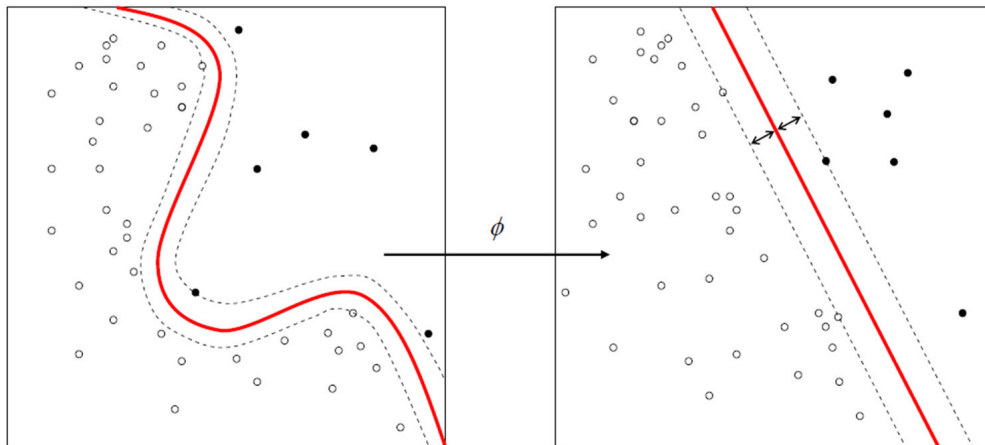


Fig.3 – From Input to Feature Space through kernel trick: the linear separation in the Feature Space (right) corresponds to a non-linear separation in the original Input Space (left)

Several types of kernel were proposed since SVM was presented (e.g. Polynomial, Radial Basis Functions, Sigmoid, etc.) each one with at least an internal parameter to be set up for mapping (Scholkopf & Smola, 2002), but choice is usually quite difficult to be optimally identified a-priori.

Many meta-heuristic approaches for optimizing parameters settings and classifiers/kernels combination have been proposed, in particular based on GA, as already mentioned (Huang & Wuang, 2006; Lessmann et al., 2006; Dioşan, 2008; He et al., 2006)

3. The Proposed Approach

In this paper, the benefits provided by an SVM classification framework, based on GA, are investigated with respect to the on-line structural health monitoring of aircrafts, in particular for the detection of possible damage and the identification of the component involved (bay or stringer). The most reliable classifier is searched for by using *Model Selection*, *Multiple Kernel Learning* and *Ensemble Learning* at the same time. Respect to the first approach, the goal is to optimize the type of kernel (among linear, Normalized Polynomial and Radial Basis Function kernel) and its internal parameter. Multiple Kernel Learning approach aims at optimizing the type of n kernels (among those afore mentioned), their related internal parameters and the coefficients of the combination of such n kernels. Finally, the goal of Ensemble Learning consists in identifying the best m SVM classifiers (type of kernels and related internal parameters, as for Model Selection) and the related m weights for their combination.

The wider is the number of configurations to be tested, the higher is the probability to obtain a reliable decision model, at the expense of higher computational time, in particular by using a simple grid-approach. The idea is to take advantages of Genetic Algorithm (GA) meta-heuristics, in order to more efficiently search for the best hyper-SVM classifier, avoiding at the same time to test bad-performing configurations.

The framework has been already proposed and validated on benchmark and real world datasets (Candelieri, 2011) as well as on a specific application in the healthcare domain, that is the early detection of destabilizations in chronic heart failure patients (Candelieri & Conforti, 2010). It proposes some variations to the traditional GA

formulation and proved that the best solution (identified among Model Selection, Multiple Kernel Learning or Ensemble Learning) strictly depends on the specific problem and the available dataset (i.e., data transformation, such as normalization, may identify a solution different from the one identified on the original dataset).

4. Experimental Results

In this study the experimental setting has been defined as follows. The detection of possible damage and the identification of the specific component affected has been defined as a two-levels binary-classification learning task. At the first level, the SVM classification framework is used to identify a classifier able to predict if strain values at the monitoring points correspond to a “damage” or a “no damage” scenario. At the second level, and only if for “damage” cases, the SVM classification framework is further used to identify a classifier able to predict if the strain values at the monitoring points (related to a damage as suggested at the first level) correspond to a “damage on bay” or a “damage on stringer”.

While the aforementioned two-levels schema represents a plausible and logical workflow, another schema proved to be reliable when Artificial Neural Network (ANN) classification learning is applied, as reported in a previous work of the authors (Candelieri et al., 2013 in press). In particular, at the first level the classification is performed between “damage on stringer” and “no damage on stringer” while, at the second level, the classification is performed between “damage on bay” and “no damage”, only if a “no damage on stringer” is predicted at the first level.

According to the two different schemes and the two different decision levels in each schema, the datasets are defined as follows:

- Schema 1:
 - Level 1: 11668 “damage” instances (3570 “damage on bay” and 8098 “damage on stringer”) versus 11668 “no damage” instances (obtained by adding Gaussian noise on the unique real instance acquired through sensors, as reported in Table 1).
 - Level 2: 3570 “damage on bay” instances versus 8098 “damage on stringer” instances.
- Schema 2:
 - Level 1: 8098 “damage on stringer” instances versus 8098 “no damage on stringer” instances (3570 “damage on bay” instances and 4528 “no damage” instances, obtained by adding Gaussian noise on the unique real instance acquired through sensors).
 - Level 2: 3570 “damage on bay” instances versus 3570 “no damage” instances (obtained by adding Gaussian noise on the unique real instance acquired through sensors).

The instances of all the aforementioned datasets are represented by 20 strain measurements acquired by 20 sensors at the corresponding monitoring points, as defined in section 2.1. Moreover, one more feature is used to characterize the class of each instance (i.e., “damage on bay”, “damage on stringer” or “no damage”).

With respect to the SVM classification framework, the following parameters setting has been used :

- $C = 1, 2, 5, 10$;
- Kernel = RBF, Normalized Polynomial, Linear;
- Degree, d (internal parameter of the Normalized Polynomial Kernel: $k(x_i, x_j) = (x_i \cdot x_j)^d$) = 2, 3, 4, 5;
- Gamma, γ (internal parameter of the RBF kernel: $k(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$) = 0.001, 0.002, 0.005, 0.007, 0.01, 0.025, 0.05, 0.075, 0.1, 0.25, 0.5, 0.75, 1, 2.5, 5, 7.5, 10, 25, 50, 75, 100, 250, 500, 750, 1000
- Coefficients (for Multiple Kernel Learning) and Weights (for Ensemble Learning) = 0.1, 0.25, 0.5, 0.75, 1.0;

Moreover, in order to mitigate the effect of random initialization in GA, several runs (30) of the SVM classification framework have been performed for each schema and level. The ANN-based approach is a previous solution proposed by the authors (Candelieri et al., 2013) and are not reported here.

The best value of the accuracy on the runs is reported as performance index and it has been used to identify the most reliable classifiers. Respect to this choice, no lack of generality occurs because the standard deviation of accuracy resulted quite limited (around 2%-3%) over the different runs. Furthermore, recall and precision resulted to be mostly balanced for all the binary-classification tasks, allowing us to consider the only accuracy as relevant performance index.

In particular:

- **Accuracy** is the number of correctly classified instances with respect to the overall number of instances
- **Recall** (for each class) is the number of correctly classified instances of a class with respect to the overall number of instances of that class
- **Precision** (for each class) is the number of correctly classified instances of a class with respect to the overall number of instances classified as belonging to that class

While Accuracy is a “global” performance index, important is the sensitivity, that is the number of correctly detected “damage situation” with respect to the overall number of instances associated to a “damage situation” (i.e., the Recall for “Damage” class at the first level of the first schema, and the Recall for “Damage on Stringer” and “Damage on Bay” classes at the first and second level of the second schema, respectively). Lower sensitivity is associated to high risk of miss-detecting potentially risky situation for the pilot.

On the other hand, giving alarms when not needed is represented by the Precision for “Damage” class at the first level of the first schema, and the Precision for “Damage on Stringer” and “Damage on Bay” classes at the first and second level of the second schema, respectively.

Each dataset has been used for both training and testing the different learning schemes; in particular a three-fold cross validation has been adopted. This approach consists in dividing each entire dataset into three not-overlapping smaller datasets, namely “folds”, while maintaining, in each fold, the same class balance of the overall dataset (stratified cross validation). In turn, each fold is used as test set while the other two are adopted as training set; the performances obtained on each test set are then averaged in order to provide the overall result.

Therefore, cross validation procedure permits to exploit each dataset both to train and test different classification approaches as well as to obtain a most reliable estimation of generalization and reliability of the trained classifiers. Although cross validation can be performed on any number of folds, such as the other well known “10-folds cross” and “leave one out” validation (where the number of folds is equal to the number of instances, that is each instance, in turn, is the test set), in this paper the three-fold cross validation has been preferred in order to maintain a low computational time for training and testing.

The proposed approach proved to be reliable because it is capable to provide high Recall (and so sensitivity) as well as high Precision for each class. Moreover, Recall and Precision measures resulted to be comparable and therefore quite similar to Accuracy.

Fig. 4 and Fig. 5 show the results provided by the proposed SVM classification framework, even compared to the results obtained in the previous work based on hierarchies of ANN.

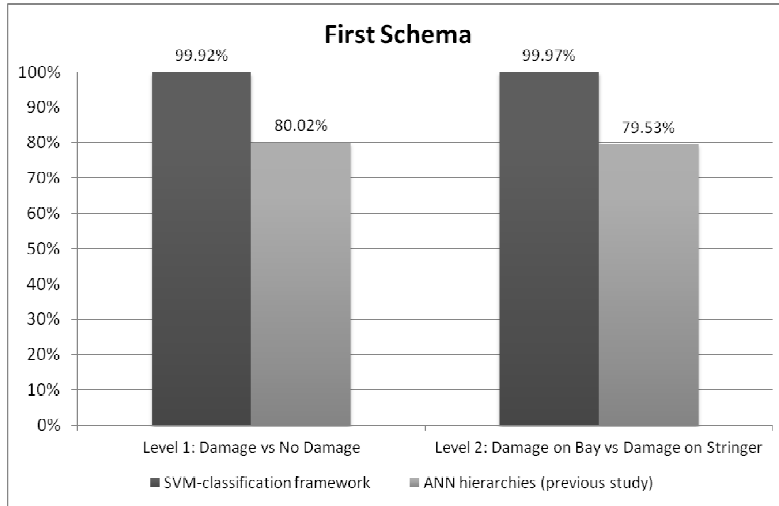


Fig.4 – Best Accuracy on 3 fold-cross validation: first schema

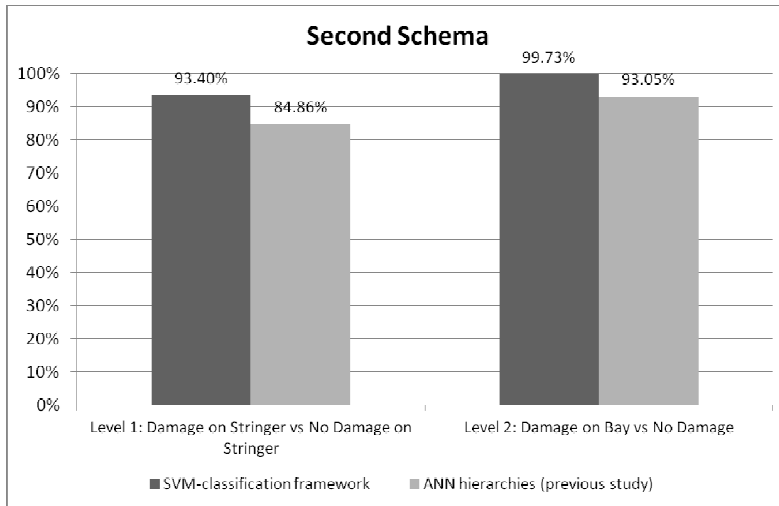


Fig.5 – Best Accuracy on 3 fold-cross validation: second schema

5. Conclusions

This paper proposes the extension of a SVM classification framework, addressing contemporary Model Selection, Multiple Kernel Learning and Ensemble Learning paradigms through GA, for implementing a reliable structural health monitoring. In particular, the framework addressed the problem of identifying a possible damage

on a helicopter fuselage panel and the involved component (i.e., bay or stringer), according to the strain field values acquired through a sensor networks deployed on the panel.

Furthermore, results have been compared with a previous approach proposed by the authors and based on hierarchies of ANNs (Candelieri et al., 2013 in press). Although the first work proved to be reliable, the new proposed approach offered better results for the specific task it addresses, allowing us to increase the reliability of the most complex system already proposed. In particular, the overall average performances of the new SVM classification framework are higher than 99% and an increase between 6% and 20% has been obtained with respect to previous results offered by ANNs.

As future works authors plan to extend the SVM classification framework to regression tasks, in order to improve also the other steps of the diagnosis and prognosis currently performed through ANN hierarchies, that are the estimation of damage centre and size (damage characterization) and the prediction of the damage evolution over time.

Furthermore, the authors also plan to adopt the SVM classification framework on more complex sensor networks by exploiting technological results already obtained in this field. For example, the SVM classification framework could be deployed on the top of a system to perform high level querying mechanisms on networks of heterogeneous sensors, as the one proposed in Giordani et al. (2010), in order to perform classification learning tasks on heterogeneous data and identify the most accurate classifier for different prediction tasks as well as the most relevant features (data sources) for a specific problem.

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