ISSN: 2639-6866

Research Article

Stem Cell Research International

An Overview of Relationship Between Muc13 With Alcohol for Pancreatic Cancer Patients

Ananya Dutta[1*] and Anuja Dutta[2]

[1]*Gauhati University, Guwahati, Assam, India-781014*

[2]*Indian Institute of Technology, Guwahati , Assam, India -781039*

***Corresponding Author**
Ananya Dutta, Gauhati University, Guwahati, Assam, India.

Submitted: 2023, Oct 01; **Accepted**: 2023, Nov 08: **Published**: 2023, Nov 10

Citation: Dutta, A., Dutta, A. (2023). An Overview of Relationship Between Muc13 With Alcohol for Pancreatic Cancer Patients. *Stem Cell Res Int, 7*(2), 166-169.

Abstract
This paper evaluates the relationship between MUC13 with respect to pancreatic cancer. MUC13 is an oncogenic mucin and its association is high in Pancreatic cancer (PC) cells treated with alcohol. This means extensive alcohol history leads to the growth of this MUC13 toxin, hence causing pancreatic cancer. Using statistical tools, this paper has developed the association between MUC-13, a carcinogen and its relationship with the increase in pancreatic cancer occurrence due to alcohol use. The dataset used is very small and consists of only 37 subjects after removing rows and columns with invalid data entries (NaN values).

Keywords: MUC13 Carcinogen, Pancreatic Cancer, Alcohol History, Feature Selection, T-SNE, Adasyn.

1. Introduction

Many researchers are in the search of biomarkers that can predict Pancreatic cancer. The Carbohydrate Antigen or the Cancer Antigen, CA 19-9 was detected in 1981 as a possible biomarker for resolution of PC. However, this CA 19-9 can have several false positives and hence is not 100% useful. Other subsequent tests may have to be done for confirmation [1]. shows that individuals who have had type-II diabetes for less than 4 years were at a 50% higher risk of contracting PC than individuals who have had type-II diabetes for greater than 4 years [2]. have concluded that subjects with long standing diabetes have a higher relative risk of PC association [3]. have also found a relationship between diabetes and PC.

Many papers debate whether it is EUS or CT that is a better detector of PC [4, 5]. have tried to detect PC via plasma protein profiling [6]. have used digital image analysis on differentiating PC and chronic pancreatitis from normal tissue [7]. have used neural network in distinguishing between PC from chronic pancreatitis [8]. have used ensemble of decision trees in detecting PCous cells from normal tissue [9]. have used digital image processing and support vector machines in differentiating PCous cells from normal tissue in EUS images [10].

The idea of the above literature study is to suggest that machine learning algorithms have delved into the realms of detection of pancreatic tumors from normal tissue. However, what is worth pointing out is that detection of these PCous cells would not be of much significance because by then, the patients would already have reached a late stage of cancer and would not survive more than a very few years. Pancreatic cancer is one of the cancers that is somewhat difficult to detect at its onset since symptoms do not show and also there are no qualifying biomarkers validated as of date. Hence there is an urgent need for a prediction model for PC to identify and precaution the high-risk group of undergoing frequent medical tests.

A huge percentage of pancreatic cancers are being detected at a late stage, giving the patient only a couple of years for survival. It has also been observed from previous works that use of synthetic chemicals, smoking and alcohol history and genetics greatly influence the occurrence of pancreatic cancer [11, 12].

2. The Dataset

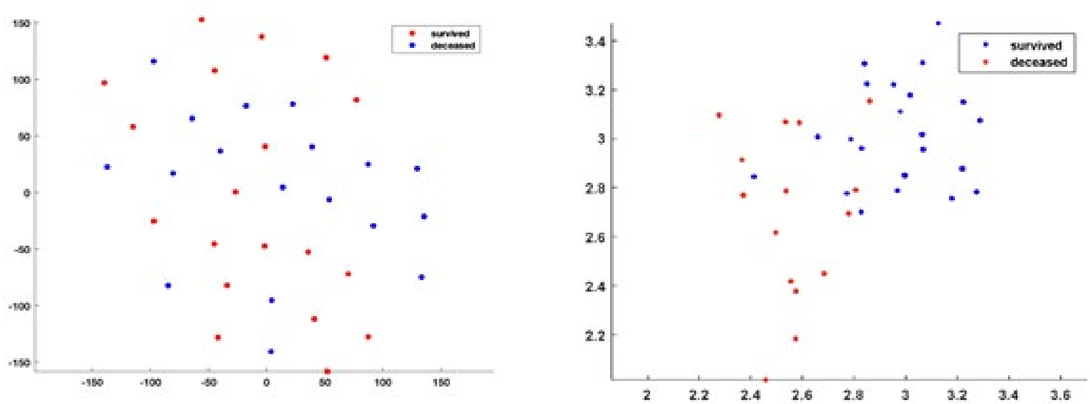
Groupings of the various values in the dataset, after being given a digital value for processing and normalized are shown in table 1.

Feature	Values
Sex	Male=1,Female=0
age	0 0.28, 0.42, 0.48, 0.57, 0.73, 1
grade	0, 0.25, 0.5, 0.75
stage	0, 1/6, 1/3
tnm	0.12, 0.16, 0.48, 0.6, 0.72, 0.84, 1
survival-status	deceased=0, survival=1
survival-months	0, 0.5, 1
MembraneMCS	0, 1/16, 2/16, 4/16, 6/16, 8/16, 9/16, 12/16, 1
CytoMCS	0, 1/9, 2/9, 4/9, 6/9, 8/9, 1
NucleusMCS	0, 1/9, 2/9, 3/9, 4/9, 6/9, 8/9, 1
OverallMCS	0.2/3, 0.4/3, 0.6/3, 1/3, 1.4/3, 1.6/3, 2.2/3, 1
SMOKING	0, 0.038/3, 0.1/3, 0.21/3, 0.328/3, 0.6/3, 1/3, 2/3, 1
DRINKING	0, 1
DIABETES	0, 1
HEPATITIS	0, 1

Table 1: Feature values in dataset

3. Results

We also observe that for mortality status=1 (that is patient survived), the value of features would be as sex=Female, age between 33-39 years, grade and stage =0. This dataset consists of 13 input parameters and 2 outputs-survival status and survival no. of months. Following are the 2D plots using t-SNE and Adasyn algorithms (considering mortality status as the output variable), as shown in figure 1.



(a) (b)

Figure 1: Figure showing 2D t-SNE and 2D ADASYN plots

4. Feature Selection

A total of 15 algorithms were used for the feature selection. Infinite Latent Feature Selection (ILFS), Infinite Feature Selection(InfFS), Eigenvector Centrality Feature Selection(ECFS), Minimum Redundancy Maximum Relevance Feature selection(mRMR), Relieff, Mutual Information Feature Selection (MutInfFS), Laplacian, Fisher, L2,1-norm Regularized Discriminative Feature Selection for Unsupervised Learning(UDFS), Feature Selection and Kernel Learning for Local Learning-Based Clustering(LLCFS), correlation based feature selection(CFS), Unsupervised Feature Selection with Ordinal Locality(UFSOL)[25], Monte Carlo Feature Selection(MCFS), Feature Selection with Adaptive Structure Learning(FSASL) [13-27].

The sum of the priorities defined by these algorithms were summed up to determine the features ranked as per their priority. The results in descending order of priority are: DRINKING, Sex, OverallMCS, NucleusMCS, MembraneMCS, HEPATITIS, Tmn, CytoMCS, Smoking, Grade, Stage, DIABETES, Age. These results were obtained after summing up the ranking given by the different feature selection algorithms and the lowest rank was the feature which has the greatest influence on Pancreatic Cancer, as shown in table 2. Hence drinking definitely influences cause of Pancreatic Cancer and also causes increase in MUC13 toxin in the cells [28–30].

	InfFS	ECFS	mrmr	relieff	mutinffs	laplacian	mcfs	fisher	UDFS	llcfs	cfs	fsasl	ufsol	dgufs	Lasso	Total(less is better)
1. Sex	1	1	12	2	12	1	3	5	13	6	2	3	12	3	4	80
2.Age	11	12	8	11	6	11	12	9	12	9	5	4	7	4	8	80
3. Grade	7	13	1	8	9	12	7	2	9	12	11	8	6	5	12	122
4. Stage	13	10	4	9	2	13	5	11	4	10	13	11	10	2	6	123
5. Tmn	12	11	7	6	8	10	9	12	7	8	3	1	5	6	7	112
6. MembraneMCS	6	8	13	5	7	6	6	4	3	1	6	9	3	7	11	95
7. CytoMCS	6	8	13	5	7	6	6	4	3	1	6	9	3	7	11	95
8. NucleusMCS	3	6	3	1	4	5	13	1	5	3	8	7	8	9	13	89
9. OverallMCS	10	5	5	3	1	9	11	10	2	5	4	5	1	10	1	82
10.Smoking	9	9	9	13	3	7	8	8	11	11	12	12	4	1	5	122
11. Drinking	9	9	9	13	3	7	8	8	11	11	12	12	4	1	5	122
12. Diabetes	5	3	11	12	13	3	2	13	8	13	9	6	9	12	9	128
13. Hepatitis	4	4	6	4	11	4	4	6	6	7	1	13	11	13	2	96

Table 2: The Features Considered in The Dataset.

5. Conclusion

Pancreatic cancer has been found to be directly influenced by smoking history, alcohol abuse, no. of cigarettes smoked in a day, genetics etc. Interestingly, there are certain other less known features, for example, sex, hepatitis -B, diabetes which are found to also influence causality of cancer in a subtle way.

Acknowledgement

The author of this paper would like to thank Dr Bonny Banerjee and Dr Chrysanthe Preza from the University of Memphis, Tennessee for their support and Dr Subhash Chauhan and Dr Sheema Khan from University of Texas, Rio Grand Valley, Texas for sharing the dataset and for their guidance in writing the paper.

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