Microarray Informatics Approach Used In Identification of Potential Drug Targets for Prostate Cancer

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ABSTRACT

The present work was carried out to find out the novel drug target in Prostate Cancer using DNA microarrays. The Microarray data analysis helps to get the gene expression profiles of Prostate Cancer. In the experiment, microarray dataset of GSE29079 i.e. the gene expression profiles of 48 normal and 47 prostate tumor tissue samples in human were extracted from database. For pre-processing data normalization was performed using the Reliability, Maintainability, and Availability (RMA) algorithm in the R (v-3.2.3) package of the Bioconductor. The normalized data was further processed by MeV(Muliple expression Viewer) for gene ontology and gene set enrichment analysis. Followed by Cytoscape, an open source bioinformatics platform which is used to study the molecular interaction networks and also visualizing of biological pathways. The current study was focused on obtaining a drug target for the cancer. The study reveals that DEGs obtained by the pathway analyses and molecular interaction networks filtered the genes that had principle pathways targeting Prostate Cancer.

Keywords: Prostate Cancer, Microarray

I. INTRODUCTION

In DNA gene expression microarrays, thousands of gene expression levels are measured simultaneously. Microarray data may provide insight into gene to gene interactions, gene function, and pathway identification. The identification of differentially expressed genes is to find genes whose expression changes in response to different biological conditions [1]. To identify genes potentially important in cancer, scientists have compared the global gene expression profiles of cancer tissue and corresponding normal tissue. Such analyses usually generate hundreds of genes differentially expressed in cancer relative to normal tissue, making it difficult to distinguish the genes that play a critical role in the neoplastic phenotype from those that are spuriously differentially expressed [2]. Prostate cancer is the most common cancer in men apart from skin cancer. The incidence of Prostate cancer has shown significant variation across the globe. Though the prevalence and characteristics of this disease have been extensively studied in many countries, data regarding the true incidence of Prostate cancer in India is limited [3].

Biological data analysis with advance computing technologies such as in computational biology approach provides diverse platforms to analyze the biomedical data for predicting differential expression level of genes in various diseased conditions. Microarray has shown to be promising method of choice, which allows the study of genes in an

organism under different conditions within a single experimental setup. The analysis of such data is performed using Bioconductor in R environment, which as a matter of fact has become the standard in the field of biomarker discovery and target identification for the effective treatment. With the emergence of microarray technology, gene expression can be measured on a genome-wide scale in cancer research by supplying tools and techniques to identify 187 significant differences in diseases[4]. This technology utilizes differential gene expression patterns in diseased and normal cells of various subtypes of cancer to identify the genes that are over-expressed and under-expressed[5]. However, this analysis produces a large amount of data, which is challenging to interpret. With the employment of modern computational and statistical analysis packages in Bioconductor and other bioinformatics tools, the data analysis has been greatly flexible in the recent years based on diverse experiments. The microarray technology has been applied to a range of applications, including discovering novel disease subtypes, developing new diagnostic tools, and identifying underlying mechanisms of disease or drug response[6]. We successfully identify potential drug targets which are strongly related to the well known drugs for prostate cancer treatment and also discover more potential drug targets which raise the attention to biologists at present. We denote that it is hard to discover drug targets based only on differential expression changes due to the fact that those genes used to be drug targets may not always have significant expression changes [7]. The set of expressed microRNAs in a given cell type, or "miRNome", can be explored under many different aspects. Many studies report modulations of the miRNome in a wide variety of cancers. Papillary thyroid cancer is the most prevalent type of endocrine cancer [8]. The datasets were downloaded in.CEL format and were analyzed on R environment (3.2.3). Most of the functionality in R is in the well-established extension packages. Most of the MA analysis packages can be found on Bioconductor (https://www.bioconductor.or g/) it is the largest growing platform for the biological data analysis and comprehension of high-throughput genomic data. R statistical programming language supports most of all the Bioconductor packages and is open source for its development [9]. Only genes meeting the selection criteria of adjusted P value <.05 were considered DEGs[10]. MultiExperiment Viewer (MeV) is a Java-based desktop application that allows advanced analysis of gene expression data through an intuitive graphical user interface[11]. Cytoscape is an open source software project for integrating biomolecular interaction networks with high-throughput expression data and other molecular states into a unified conceptual framework. Although applicable to any system of molecular components and interactions, Cytoscape is most powerful when used in conjunction with large databases of protein-protein, protein-DNA, and genetic interactions that are increasingly available for humans and model organisms[12].

II METHODOLOGY

The objective of the research was to identify novel targets and ligands for Prostate cancer through Microarray data analysis and structure based virtual screening. Methodology involves two parts:

2.1 Analysis of Microarray Data

- 1.1 Data collection from Gene Expression Omnibus(GEO-NCBI)
- 1.2 Normalisation in R(Bioconductor Package)
- 1.3 Statistical tests(T-test) using Multi Expression Viewer(MeV)
- 2. Target identification and Virtual Screening of compound library for finding good ligand
 - 2.1 Building a network in cytoscape
 - 2.2 Finding a good lead by screening library of compounds (Lipinki's screening) Various online, offline tools

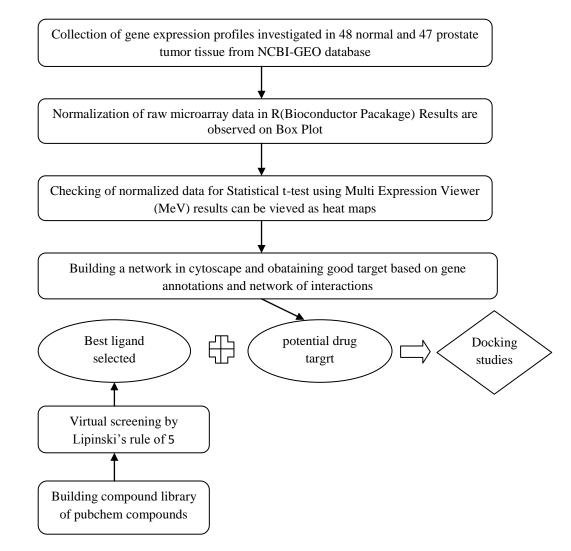


Figure 1. Schematic diagram of the flow chart for drug target identification and ligand binding, docking studies of target and ligands

Analysis of Microarray Data

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1.1-Data collection from Gene Expression Omnibus (NCBI-GEO) - GSE29079

The gene expression datasets were downloaded from NCBI's GEO database. The dataset GSE29079 downloaded consisted of samples taken from normal cells and cancer patients. The data consists large-scale gene expression profiles investigated in 48 normal and 47 prostate tumor tissue samples using Affymetrix GeneChip Exon 1.0 ST microarrays[8]. The datasets were downloaded in .cell format and were analyzed on R environment.

1.2-Normalization of raw microarray data in R(Bioconductor Pacakage)

Most of the Microarray analysis packages can be found on Bioconductor it is the largest growing platform for the biological data analysis and comprehension of high-throughput genomic data. To check the quality and detect the outlier within the samples in the dataset, diagnostic plots such as box plots were plotted. These plots give a quick view of the normalized log2 intensities[9]. In the current work, the data normalization was performed using Reliability, Maintainability, and Availability (RMA). RMA, consist of several steps: background correction, normalization of probes, and summarization where individual probes are combined into a probe set. RMA is useful for highly precise estimates of expression. To identify the differentially expressed genes DEGs in normal and cancer cell lines an adjusted P-Value ≤ 0.05 was used as cut-off criteria [10].

1.3-Checking of normalized data for Statistical t-test using Multi Expression Viewer (MeV)-MeV is a desktop application for the analysis, visualization and data-mining of large-scale genomic data. It is a versatile microarray tool, incorporating sophisticated algorithms for clustering, visualization, classification, statistical analysis and biological theme discovery [11]. A huge array of alrogithms are included in MeV modules, and are available at a button-click, such as K-means clustering, Hierarchical clustering, t-Tests, Significance Analysis of Microarrays, Gene Set Enrichment Analysis, and EASE. It generates information of gene expressions and annotation data from single or multiple experiments.

2.2. Lead and Target identification

2.1- Network building with cytoscape

Cytoscape is a open source bioinformatics software platform for viewing networks of molecular interaction and biological pathways and integrating these networks with annotations, gene expression profiles and other state data. The coexpression network of these DEGs was then visualized using Cytoscape (version 3.2.0, U.S. National Institute of General Medical Sciences, http://cytoscape.org/), an open source software for integrating biomolecular interaction networks. In the network, a "node" represents a gene or protein, and a "line "represents an interaction between 2 nodes. The degree of each node equals the number of nodes that interact with it [12]. Cytoscape is a general platform for complex network analysis and visualization. Genes were studied for the uniqueness in the pathways involved and the TARGET was selected for docking.

2.2 Building a compound library and Finding a good lead by screening library of compounds, Virtual screening to determine best leads(ligand) to target:

A compound library was made which had around 200 anti-cancerous compounds and 3D structure was downloaded from Pubchem, and Chemspider as SDF or Mol files. The target selected for Prostate Cancer in the study was GAPDH [Glyceraldehyde 3-Phosphate Dehydrogenase] based on annotations from cytoscape network. Virtual screening was done to determine the best lead which binds at appropriate sites with target. Virtual screening is a computational technique used in drug discovery research. With computers, it quickly searches a large libraries of chemical structures to identify the structures which are most likely to bind to a drug target, typically a protein receptor or enzyme. The aim of virtual screening is to identify molecules of novel chemical structure that bind to the macromolecular target of interest [13]. Lipinski's screening based on Lipinski's rule of 5 for 200 anti-cancerous compounds was done the obtained scores like Molecular Weight. H-Bond Donor, H-Bond Acceptor, XLogP were screened for further analysis. The molecular weight of the compound selected should be less than 500g/mol, H-bond donor should be less than H-acceptor should be less than 10, & Xlog P should not be more than 5[14].

These screened leads were used for Auto Docking. Using AutoDock Vina all compounds were docked one by one with the target and grid box with particular dimensions was set by preparing conf.txt file. Select the ligand and torsions and save the file as .pdbqt files. According to the existing drug dock score for the disease, the best dock scores were selected. Docking scores for each ligand were noted. And based on the existing drug docks scores, the best dock scores were selected[15]. The online tool preADME was used to study ADMET properties and toxicity of selected compounds[16]. Results of all tools are attached in results section. The structures of the leads are included in the results section.

III RESULTS AND DISCUSSION

The current work describes a microarray approach for identification of a suitable drug target. The data from prostate cancer was collected from NCBI-GEO.the following figure gives an idea of microarray data collection.

	Gene Expression Omnibus				
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Scope: Self	Format: HTML Amount: Quick GEO accession: gse29079 Ouery DataSets for GSE29079				
Status	Public on Dec 31, 2011				
Title	Gene expression profiles of 48 normal and 47 prostate tumor tissue samples				
Organism	formo sapiens				
Experiment type	Expression profiling by array				
Summary	Large-scale gene expression profiles were investigated in 48 normal and 47 prostate tumor tissue samples using Affymetrix GeneChip Exon 1.0 ST microarrays.				
Overall design	Gene expression profiling of human prostate samples using Affymetrix Human Exon 1.0 ST arrays				
	Two disease subtype analyses were performed:				
	 Prostate Tumor vs Benign TMPRSS2-ERG fusion-positive vs fusion-negative prostate tumors 				
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Figure 2. Retrival of dataset of gene expression profiles of normal and prostate cancer tissue cells from NCBI-

GEO

The quality control analysis involves the assessment of the data and detection of the outliers. In the work, the normalization of the data was performed using Reliability, Maintainability, and Availability (RMA). The typical preprocessing method, RMA consist of several stepswhich were performed serially- background correction, normalization of probes and summarization where individual probes are combined into a probe set. The boxplot of the raw data represents the distribution of log2 intensities across all the samples. The boxplot of normalized signal intensities across all samples was carried out and the fig shows the normalized data.

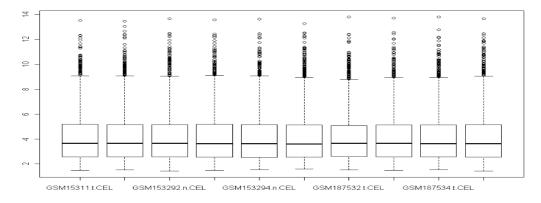


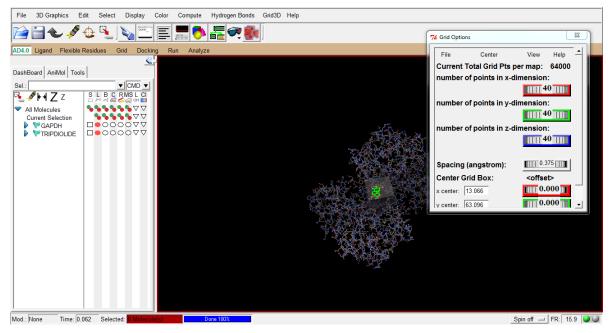
Figure 3. The boxplot showing the summarized log2 intensities on the y-axis and the distribution of 2 Normal cells and 3 Prostate cancer/ tumor cell line samples for the raw data.

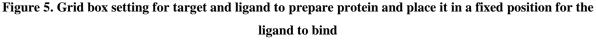
The DEGs were identified by MeV the package was used to build the model matrix with defined contrasts and an adjusted false discovery rate to analyze the gene. Expression analysis profiles of normal and Prostate cancer dataset led to identification of DEGs, that were found to be differentially expressed with an adjusted an $P \le 0.05$ based on t-test on the normalized resultant data.

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Figure 4. Pathway clustering of DEGs using Cytpscape to study the pathway analysis.

The clustering and pathway enrichment of DEGs The functional classification of the obtained DEGs was performed with the online biological classification Cytoscape. After performing Mev analyzing the network of pathways in Cytoscape Glyceraldehyde 3-phosphate dehydrogenase (GAPDH) is the target as selected. Molecular Docking of the Proteins. The current study was further reinforced by performing comparative docking studies of the novel proteins with the ligands from ligand library. The molecular docking study was performed on protein target name and a set of 10 chemical compounds retrieved from pubchem database using both Autodock vina. For creation of gpf, grid parameter file and dpf, docking parameter file using Autodock, the polar hydrogen atoms, Kollman charges parameters were set. For ligand the preparation before docking were done like detecting and choosing tortion tree. Grid setting plays an important role in docking because here one can decide the XYZ coordinates of the amino acids in the target for ligand binding. Binding affinities from docking were compared between target protein and against the corresponding chemical compound are tabulated in the table 1. Top docking pose, consider the binding energy (lowest) E-total, and the affinity interactions with active site of the protein. Since the E-total of the compound Id CID 294491 is -0.01, i.e Tripdiolide with molecular weight 376.405 g/mol was the effective ligand obtained. The grid box was set with X-centre: 13.066, Y-centre: 63.096, and Z-centre: 16.472 as shown in the figure 5 below. The lead obtained is suitable to bind to the target GAPDH in order to prevent the prostate cancer.





Compound id	Affinity	E-total
cid_294491	-10.3	-0.01
cid_5351344	-10.2	-0.04
cid_83843	-10.2	-345.28
cid_105111	-10.2	-221.65
cid_54678486	-9.0	-552.60
cid_4042	-8.3	-21.49
cid_8530	-7.9	-306.81
cid_9064	-7.2	-262.81
cid_382831	-6.9	-306.81
cid_9817550	-5.4	-471.78

Table 1: The affinity and binding energy scores obtained for the selected 10 ligands for docking with the target.

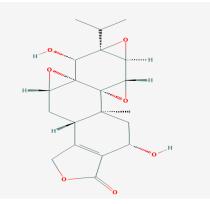


Figure 6. Structure of tripdiolide with Pubchem ID CID 294491

Number of studies state the role of GAPDH in Prostate cancer. Glyceraldehyde-3-phosphate dehydrogenase enhances transcriptional activity of androgen receptor in prostate cancer cells [17]. Studies have reported that the tripdiolide provides a method of effecting immunosuppression, and a method of inducing apoptosis in a cell, which is useful in antiproliferative therapy, especially anticancer therapy [18].

IV CONCLUSION

Generally, microarrays have expression levels for several thousand genes, and it is required to filter out those that are not significant. It is an important step before any further processing, such as clustering, to identify genes that are differentially expressed. The work focused on finding the best gene target, which can give better prediction

accuracy for Prostate cancer. The best target as selected based on its role of cancer development was GAPDH i.e Glyceraldehyde 3-phosphate dehydrogenase. Finally, the work provides the best lead to the target by performing Virtual Screening of the natural anti cancer compounds.

Glyceraldehyde 3-phosphate dehydrogenase (GAPDH) is the target as obtained after performing Mev and Cytoscape. Tripdiolide with molecular weight 376.400g/mol which is suitable to bind to the target GAPDH in order to prevent the prostate cancer. The present study has thus led to the identification of protein that can be targeted for effective drug design and vaccine development against prostate cancer.

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