In Silico Genetics Revealing Novel Mutations in CEBPA Gene Associated with Acute Myeloid Leukemia

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Abstract:
Background: Myelodysplastic syndrome/Acute myeloid leukemia (MDS/AML) is a highly heterogeneous malignant disease; affects children and adults of all ages. AML is one of the main causes of death in children with cancer. However, It is the most common acute leukemia in adults, with a frequency of over 20 000 cases per year in the United States of America alone.

Methods: The SNPs were retrieved from the dbSNP database. this SNPs were submitted into various functional analysis tools that done by SIFT, PolyPhen-2, PROVEAN, SNAP2, SNPs&GO, PhD-SNP and PANTHER, while structural analysis were done by I-mutant3 and MUPro. The most damaging SNPs were selected for further analysis by Mutation3D, Project hope, ConSurf and BioEdit softwares. Results: A total of five novel nsSNPs out of 248 missense mutations were predicted to be responsible for the structural and functional variations of CEBPA protein. Conclusion: In this study the impact of functional SNPs in the CEBPA gene was investigated through different computational methods, which determined that (R339W, R288P, N292S N292T and D63N) are novel SNPs have a potential functional effect and can thus be used as diagnostic markers and may facilitate in genetic studies with a special consideration of the large heterogeneity of AML among the different populations.

Keywords: Myelodysplastic syndrome (MDS), acute myeloid leukemia (AML), malignant disease, myeloid malignancy, CEBPA, in silico analysis, diagnostic markers.
1. Introduction:

Myelodysplastic syndrome/Acute myeloid leukemia (MDS/AML) is a highly heterogeneous malignant disease; affects children and adults of all ages. AML is one of the main causes of death in children with cancer. (1-5) However, it is the most common acute leukemia in adults, (6-8) with a frequency of over 20,000 cases per year in the United States of America alone. (6) It is characterized by familial platelet disorder with propensity to myeloid malignancy. (2) AML is frequently caused by mutation in CEBPa gene. (9-13) The CCAAT/enhancer-binding protein-alpha (CEBPα) is a transcription element that influences immune cell fate and differentiation. (14, 15) Most AML patients with CEBPa mutations simultaneously carry double mutations. (16-18) Nevertheless, different mutations have been documented. (19-23) Some studies have been reported which claimed some related factors besides CEBPa mutation, such as Smoking, alcohol and exposure to solvents and agrochemicals may cause AML, (24-26) but no evidence of publication bias. Other genes have been reported which cause AML such as FLT3-ITD and NMP1 which helped refine individual prognosis. Furthermore, these mutant molecules characterize as a potential targets for molecular therapies. (6, 27-30) Sometimes, chronic lymphocytic leukemia patients can develop AML. (31) While in rare cases AMLs can develop esophageal cancer. (32)

Stem-cell transplantation treatment is associated with the outcome of treatment for patients with cytogenetically normal AML. (33) Nevertheless, the benefit of the transplant was limited to the subgroup of patients with the prognostically adverse genotype consisting of wild-type CEBPA without FLT3-ITD. (30, 33) In spite of this hopeful recent evolution, the outcomes of patients with AML remain insufficient, with more than fifty percent of patients eventually dying from this devastating disease. The aim of this study is to identify functional SNPs located in coding region of CEBPA gene using in silico analysis.

Disease-causing SNPs are often found to occur at evolutionarily conserved regions. Those have a crucial role for protein structure and function. The ability to predict whether a particular SNP is disease-causing or not is of great importance for the early detection of disease. (34-44) The practice of translational bioinformatics has solid influence on the identification of candidate SNPs and can contribute in pharmacogenomics by identifying high risk SNP mutation contributing to drug response as well as developing novel therapeutic elements for this deadly disease. (45-53) This is the first in silico analysis in the coding region of CEBPA gene that prioritized nsSNPs to be used as a diagnostic markers with a special consideration of the large heterogeneity of AML among the different populations.

2. Materials and methods:

2.1. Data mining:

The Polymorphic data on SNPs of human CEBPa gene was collected from NCBI web site. (https://www.ncbi.nlm.nih.gov/) and the human protein sequence was collected from Uniprot (https://www.uniprot.org/). (54)
2.2. Functional analysis:

Functional impacts of nsSNPs were predicted using the following in silico tools:

2.2.1. SIFT:

SIFT was used to observe the effect of Amino Acids variants on protein on functional level. SIFT predicts damaging SNPs on the basis of the degree of conserved amino A.A. residues in aligned sequences to the closely related sequences, gathered through PSI-BLAST.(55) It is available at (http://sift.jcvi.org/).

2.2.2. PolyPhen-2:

PolyPhen-2 stands for polymorphism phenotyping (version 2). PolyPhen-2 was used to observe the influences of Amino Acids substitution on structural and functional level of the protein by considering physical and comparative approaches.(56) It is available at (http://genetics.bwh.harvard.edu/pph2/).

2.2.3. PROVEAN:

PROVEAN is a software tool which predicts whether an amino acid substitution has an impact on the biological function of a protein. It is useful for filtering sequence variants to identify nonsynonymous variants.(57) It is available at (https://rostlab.org/services/snap2web/).

2.2.4. SNAP2:

SNAP2 is a trained classifier that is based on a machine learning device called "neural network". It distinguishes between effect and neutral variants/non-synonymous SNPs by taking a variety of sequence and variant features into account. It is available at (https://rostlab.org/services/snap2web/).

2.2.5. SNPs&GO:

SNPs&GO is an accurate method that, starting from a protein sequence, can predict whether a variation is disease related or not by exploiting the corresponding protein functional annotation. SNPs&GO collects in unique framework information derived from protein sequence, evolutionary information, and function as coded in the Gene Ontology terms, and underperforms other available predictive methods (PHD-SNP and PANTHER).(58) It is available at (http://snps.biofold.org/snps-and-go/snps-and-go.html).
2.2.6. I-Mutant 3.0:

I-Mutant 3.0 is a neural network based tool for the routine analysis of protein stability and alterations by taking into account the single-site mutations. The FASTA sequence of protein retrieved from UniProt is used as an input to predict the mutational effect on protein stability. It is available at [http://gpcr2.biocomp.unibo.it/cgi/predictors/I-Mutant3.0/IMutant3.0.cgi](http://gpcr2.biocomp.unibo.it/cgi/predictors/I-Mutant3.0/IMutant3.0.cgi).

2.2.7. MUpro:

MUpro is a support vector machine-based tool for the prediction of protein stability changes upon nonsynonymous SNPs. The value of the energy change is predicted, and a confidence score between -1 and 1 for measuring the confidence of the prediction is calculated. A score <0 means the variant decreases the protein stability; conversely, a score >0 means the variant increases the protein stability. It is available at [http://mupro.proteomics.ics.uci.edu/](http://mupro.proteomics.ics.uci.edu/).

3. Structural Analysis:

3.1. Detection of nsSNPs Location in Protein Structure:

Mutation3D is a functional prediction and visualization tool for studying the spatial arrangement of amino acid substitutions on protein models and structures. Further, it presents a systematic analysis of whole genome and whole-exome cancer datasets to demonstrate that mutation3D identifies many known cancer genes as well as previously underexplored target genes. It is available at [http://mutation3d.org](http://mutation3d.org).

4. Modeling nsSNP locations on protein structure:

Project hope is a web-server to search protein 3D structures (if available) by collecting structural information from a series of sources, including calculations on the 3D coordinates of the protein, sequence annotations from the UniProt database, and predictions by DAS services. Protein sequences were submitted to project hope server in order to analyze the structural and conformational variations that have resulted from single amino acid substitution corresponding to single nucleotide substitution. It is available at [http://www.cmbi.ru.nl/hope](http://www.cmbi.ru.nl/hope).

5. Conservational analysis:

5.1. ConSurf server:

ConSurf web server provides evolutionary conservation profiles for proteins of known structure in the PDB. Amino acid sequences similar to each sequence in the PDB were collected and multiply aligned using CSI-BLAST and MAFFT, respectively. The evolutionary conservation of
each amino acid position in the alignment was calculated using the Rate 4Site algorithm, implemented in the ConSurf web server.\(^{(62)}\) It is available at \(\text{http://consurf.tau.ac.il/}\).

5.2. BioEdit:

BioEdit software is intended to supply a single program that can handle most simple sequence and alignment editing and manipulation functions as well as a few basic sequences analyses. It is available for download at \(\text{http://www.mbio.ncsu.edu/bioedit/bioedit.html}\).

![Figure (1): Descriptive Workflow Software’s used in SNPs analysis.](image)

3. Results:

248 missense mutation were retrieved from the dbSNP/NCBI Database, this SNPs were submitted into various functional analysis tools that done by SIFT, PolyPhen-2, PROVEAN and SNAP2. SIFT server represented 28 deleterious SNPs, PolyPhen-2 represented 85 damaging SNPs (29 were possibly damaging and 56 were probably damaging to protein), PROVEAN represented 34 deleterious SNPs while in SNAP2 we filtered the triple-positive deleterious SNPs from the previous three analysis tools, out of 53 There were 19 nsSNPs predicted deleterious SNPs by SNAP2. Table (1) represent the Quarter-positive of deleterious SNPs after filtrations of
them the number decreased rapidly to 19 SNP after this submitted them into SNPs&GO and PhD-SNP and PANTHER to run more investigation on this SNP and their effect on the functional level. The triple positive in the three tools were 5 disease-associated SNPs, that shown in Table (2). Finally, we submitted them to I-Mutant 3.0, P-MUT and MUPro respectively (Table 3) to investigate their effect on structural level. All the SNPs were found to cause a decrease in the stability of the protein.

Table (1): Affect or damaging nsSNPs associated predicted by various softwares:

| dbSNP rs#       | SUB   | SIFT PREDICTION | Score | Polyphen prediction | Score | PROVEAN Prediction | Score | SNAP2 Prediction | Score |
|-----------------|-------|-----------------|-------|---------------------|-------|--------------------|-------|------------------|-------|
| rs1358286265    | G355V | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -7.083| effect           | 48    |
| rs1402033817    | G355S | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -4.501| effect           | 47    |
| rs1439202716    | R343C | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -6.702| effect           | 43    |
| rs1455027551    | R339W | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -7.798| effect           | 74    |
| rs758726582     | R333C | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -7.409| effect           | 14    |
| rs1422138876    | V328G | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -6.823| effect           | 51    |
| rs1306818311    | R327W | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -6.468| effect           | 47    |
| rs781549846     | R325C | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -6.324| effect           | 19    |
| rs1013241741    | S299C | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -4.866| effect           | 23    |
| rs1391793930    | K298R | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -2.924| effect           | 31    |
| rs1392203731    | K298Q | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -3.899| effect           | 34    |
| rs776590829     | N292T | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -5.788| effect           | 35    |
| rs781549846     | R325C | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -4.907| effect           | 29    |
| rs1064794962    | R288P | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -6.636| effect           | 66    |
| rs796586647     | E284D | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -2.694| effect           | 44    |
| rs1196766447    | E284A | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -5.588| effect           | 18    |
| rs1352573347    | P233H | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -3.924| effect           | 37    |
| rs1267025311    | R156W | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -2.983| effect           | 71    |
| rs1452063514    | D63N  | AFFECT          | 0     | Damaging            | 1     | Deleterious        | -2.992| effect           | 72    |

Table (2): Pathogenic nsSNPs associated variations predicted by predicted by various softwares:

| SUB   | SNPs&GO Prediction | RI | Probability | PANTHER Prediction | RI | Probability | PHD-SNP Prediction | RI | Probability | P-mut Prediction | Probability |
|-------|--------------------|----|-------------|--------------------|----|-------------|--------------------|----|-------------|------------------|-------------|
| R339W | Disease            | 1  | 0.539       | Disease            | 9  | 0.949       | Disease            | 2  | 0.615       | Disease          | 0.85 (91%) |
| N292T | Disease            | 5  | 0.723       | Disease            | 10 | 0.985       | Disease            | 4  | 0.749       | Disease          | 0.85 (91%) |
| N292S | Disease            | 0  | 0.751       | Disease            | 10 | 0.98        | Disease            | 5  | 0.767       | Disease          | 0.85 (91%) |
| R288P | Disease            | 4  | 0.704       | Disease            | 7  | 0.86        | Disease            | 7  | 0.872       | Disease          | 0.85 (91%) |
| D63N  | Disease            | 4  | 0.717       | Disease            | 9  | 0.94        | Disease            | 4  | 0.697       | Disease          | 0.67 (85%) |

*RI: Reliability Index*
Table (3): stability analysis predicted by I-Mutant version 3.0 and MUPro:

| dbSNP rs#   | SUB | SVM2 Prediction Effect | RI | DDG Value Prediction | MUPro Prediction | MUPro Score |
|------------|-----|------------------------|----|----------------------|------------------|-------------|
| rs1455027551 | R339W | Decrease               | 3  | -0.21                | Decrease         | -0.24675    |
| rs776590829  | N292T | Increase               | 2  | -0.35                | Decrease         | -1.48124    |
|             | N292S | Decrease               | 6  | -0.73                | Decrease         | -1.46979    |
| rs1064794962 | R288P | Decrease               | 5  | -0.73                | Decrease         | -0.66005    |
| rs1452063514 | D63N | Increase               | 1  | -0.2                 | Decrease         | -1.22302    |

Figure (2): Structural simulations for wild type CEBPA gene, demonstrated by Mutation3D.

Figure (3): In the 3D-structure can be seen that the wild-type residue is located in an α-helix.
Figure (4): Conserver regions in CEBPA protein were determined using Consurf web server.
Figure (5): Alignments of 8 amino acid sequences of CEBPA representing that the residues predicted to be mutated are evolutionarily conserved across species.

4. Discussion:

This study revealed 5 novel mutations in CEBPA gene using different sequence and structure-based algorithms. Figure (1). Single Nucleotide Polymorphisms (SNP) that found in this study could be used in prognostics of disease, because identification of CEBPA status in AML has major clinical importance, allowing relapse risk to be stratified properly for post-remission treatment.(63, 64)

All these SNPs (R339W, R288P, N292S N292T and D63N) were retrieved from dbSNPs/NCBI database as untested, were found to be all novel pathogenic mutations.

CEBPA gene provides instructions for making a protein called CCAAT enhancer binding protein alpha. This protein is a transcription factor and it is act as a tumor suppressor, which means that it is involved in cellular mechanisms that help prevent the cells from growing and dividing too rapidly or in an uncontrolled way and that is the principle of cancer (AML). (23, 65)

We also achieved analysis by Mutation3D server, All SNPs in red (R288P, N292S and N292T) are clustered mutation. Significantly, such mutation clusters are frequently associated with human cancers.(66) While SNPs in blue (R339W) and gray (D63N) are covered and uncovered mutations respectively. (Figure 2)

Project HOPE software was used to submit the most damaging SNPs, (D63N) is the only SNP is located on the surface of a domain, Asparagine (The mutant residue) charge is neutral
while Aspartic Acid (the wild-type residue) charge was negative. The charge of the wild-type residue is lost by this mutation; This can cause loss of interactions with other molecules. The mutation is located within a stretch of residues required to repress E2F1:TFDP1-mediated transcription, to inhibit cell cycle and to induce adipocyte differentiation. The differences in amino acid properties can disturb this region and disturb its function. In the second SNP (N292S): The mutated residue is located in a domain that is important for the activity of the protein and in contact with residues in another domain. It is possible that this interaction is important for the correct function of the protein. The mutation can affect this interaction and as such affect protein function. In the third SNP (N292T): The mutation is located within a domain, annotated in UniProt as: bZIP. The mutation introduces an amino acid with different properties, which can disturb this domain and abolish its function. In the fourth SNP (R288P): Proline disrupts an α-helix when not located at one of the first 3 positions of that helix. In case of the mutation at hand, the helix will be disturbed and this can have severe effects on the structure of the protein. (Figure 3)

We also used ConSurf web server; the nsSNPs that are showed by black box located at highly conserved amino acid positions have a tendency to be the most damaging nsSNPs. (Figure 4) In this study we also observed that, only one SNP (D63N) the residue predicted to be mutated is evolutionarily conserved across species. (Figure 5)

This study is the first in silico analysis while all other previous studies were NSG analysis, in vitro analysis and in vivo analysis (13, 64, 67, 68)

This study is the first in silico analysis was focused in coding region which revealed five novel mutations that have a possible functional effect and may therefore be used as diagnostic markers for Acute myeloid leukemia and may create an ideal target for cancer therapy. These findings combined with detailed understanding of normal human and murine haematopoiesis makes Acute myeloid leukemia an outstanding model for understanding the principles of cancer progression.(69, 70) Lastly wet lab techniques are recommended to support these findings.

**Conclusion:**
In this study the impact of functional SNPs in the CEBPA gene was investigated through different computational methods, which determined that (R339W, R288P, N292S N292T and D63N) are novel SNPs have a potential functional effect and can thus be used as diagnostic markers. And may facilitate in genetic studies with a special consideration of the large heterogeneity of AML among the different populations. Future studies are needed to confirm those SNPs and identify relevant contributors to disease pathogenesis. This study increased understanding of the pathogenesis of AML by bioinformatics analysis, and may create an ideal target for cancer therapy.
Competing Interests:

The authors declare no conflict of interest.

Data Availability:

All data underlying the results are available as part of the article and no additional source data are required.

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References:

1. Chaudhury S, O’Connor C, Canete A, Bittencourt-Silvestre J, Sarrou E, Prendergast A, et al. Age-specific biological and molecular profiling distinguishes paediatric from adult acute myeloid leukaemias. Nature communications. 2018;9(1):5280.
2. Liew E, Owen C. Familial myelodysplastic syndromes: a review of the literature. Haematologica. 2011;96(10):1536-42.
3. Short NJ, Rytting ME, Cortes JE. Acute myeloid leukaemia. Lancet (London, England). 2018;392(10147):593-606.
4. Falini B, Martelli MP. Impact of genomics in the clinical management of patients with cytogenetically normal acute myeloid leukemia. Best practice & research Clinical haematology. 2015;28(2-3):90-7.
5. Masetti R, Castelli I, Astolfi A, Bertuccio SN, Indio V, Togni M, et al. Genomic complexity and dynamics of clonal evolution in childhood acute myeloid leukemia studied with whole-exome sequencing. Oncotarget. 2016;7(35):56746-57.
6. De Kouchkovsky I, Abdul-Hay M. 'Acute myeloid leukemia: a comprehensive review and 2016 update'. Blood cancer journal. 2016;6(7):e441.
7. Hirsch CM, Przychodzen BP, Radivojevitch T, Patel B, Thota S, Clemente MJ, et al. Molecular features of early onset adult myelodysplastic syndrome. Haematologica. 2017;102(6):1028-34.
8. Tomizawa D. Acute leukaemia in adolescents and young adults. [Rinsho ketsueki] The Japanese journal of clinical hematology. 2017;58(10):2160-7.
9. Akin DF, Oner DA, Kurekci E, Akar N. Determination of CEBPA mutations by next generation sequencing in pediatric acute leukemia. Bratislavské lekarske listy. 2018;119(6):366-72.
10. Green CL, Koo KK, Hills RK, Burnett AK, Linch DC, Gale RE. Prognostic significance of CEBPA mutations in a large cohort of younger adult patients with acute myeloid leukaemia: impact of double CEBPA mutations and the interaction with FLT3 and NPM1 mutations. Journal of clinical oncology : official journal of the American Society of Clinical Oncology. 2010;28(16):2739-47.
11. Steffen B, Muller-Tidow C, Schwable J, Berdel WE, Serve H. The molecular pathogenesis of acute myeloid leukemia. Critical reviews in oncology/hematology. 2005;56(2):195-221.
12. Kato N. [Analysis of leukemogenesis induced by C/EBPalpha mutations]. [Rinsho ketsueki] The Japanese journal of clinical hematology. 2011;52(6):320-8.
13. Mueller BU, Pabst T. C/EBPalpha and the pathophysiology of acute myeloid leukaemia. Current opinion in hematology. 2006;13(1):7-14.
14. Leroy H, Roumier C, Huyghge P, Biggio V, Fenaux P, Preudhomme C. CEBPA point mutations in hematological malignancies. Leukemia. 2005;19(3):329-34.
15. Kasakura K, Takahashi K, Itoh T, Hosono A, Nunomura S, Ra C, et al. C/EBPalpha controls mast cell function. FEBS letters. 2014;588(24):4645-53.
16. Wouters BJ, Lowenberg B, Erpelinck-Verschueren CA, van Putten WL, Valk PJ, Delwel R. Double CEBPA mutations, but not single CEBPA mutations, define a subgroup of acute myeloid leukemia with a distinctive gene expression profile that is uniquely associated with a favorable outcome. Blood. 2009;113(13):3088-91.
17. Pabst T, Mueller BU. Complexity of CEBPA dysregulation in human acute myeloid leukemia. Clinical cancer research : an official journal of the American Association for Cancer Research. 2009;15(17):5303-7.
18. van Vliet MH, Burgmer P, de Quartel L, Brand JP, de Best LC, Vietor H, et al. Detection of CEBPA double mutants in acute myeloid leukemia using a custom gene expression array. Genetic testing and molecular biomarkers. 2013;17(5):395-400.
19. Schwieger M, Lohler J, Fischer M, Herwig U, Tenen DG, Stocking C. A dominant-negative mutant of C/EBPalpha, associated with acute myeloid leukemias, inhibits differentiation of myeloid and erythroid progenitors of man but not mouse. Blood. 2004;103(7):2744-52.
20. Asou H, Gombart AF, Takeuchi S, Tanaka H, Tanioka M, Matsui H, et al. Establishment of the acute myeloid leukemia cell line Kasumi-6 from a patient with a dominant-negative mutation in the DNA-binding region of the C/EBPalpha gene. Genes, chromosomes & cancer. 2003;36(2):167-74.
21. Schuster MB, Porse BT. C/EBPalpha in leukemogenesis: identity and origin of the leukemia-initiating cell. BioFactors (Oxford, England). 2009;35(3):227-31.
22. Shiba N, Yoshida K, Shiraishi Y, Okuno Y, Yamato G, Hara Y, et al. Whole-exome sequencing reveals the spectrum of gene mutations and the clonal evolution patterns in paediatric acute myeloid leukaemia. British journal of haematology. 2016;175(3):476-89.
23. Schlenk RF, Dohner K, Krauter J, Frohling S, Corbacioglu A, Bullinger L, et al. Mutations and treatment outcome in cytogenetically normal acute myeloid leukemia. The New England journal of medicine. 2008;358(18):1909-18.
24. Khan IA, Mort M, Buckland PR, O'Donovan MC, Cooper DN, Chuzhanova NA. In silico discrimination of single nucleotide polymorphisms and pathological mutations in human gene promoter regions by means of local DNA sequence context and regularity. In silico biology. 2006;6(1-2):23-34.
25. Kucukkal TG, Yang Y, Chapman SC, Cao W, Alexov E. Computational and experimental approaches to reveal the effects of single nucleotide polymorphisms with respect to disease diagnostics. International journal of molecular sciences. 2014;15(6):9670-717.
37. Qu HQ, Lawrence SG, Guo F, Majewski J, Polychronakos C. Strand bias in complementary single-nucleotide polymorphisms of transcribed human sequences: evidence for functional effects of synonymous polymorphisms. BMC genomics. 2006;7:213.
38. Qiu P. Recent advances in computational promoter analysis in understanding the transcriptional regulatory network. Biochemical and biophysical research communications. 2003;309(3):495-501.
39. Rost B. Twilight zone of protein sequence alignments. Protein engineering. 1999;12(2):85-94.
40. Ng PC, Henikoff S. Predicting deleterious amino acid substitutions. Genome research. 2001;11(5):863-74.
41. Saunders CT, Baker D. Evaluation of structural and evolutionary contributions to deleterious mutation prediction. Journal of molecular biology. 2002;322(4):891-901.
42. Pei J, Grishin NV. Combining evolutionary and structural information for local protein structure prediction. Proteins. 2004;56(4):782-94.
43. Yue P, Moult J. Identification and analysis of deleterious human SNPs. Journal of molecular biology. 2006;356(5):1263-74.
44. Capriotti E, Calabrese R, Casadio R. Predicting the insurgence of human genetic diseases associated to single point protein mutations with support vector machines and evolutionary information. Bioinformatics (Oxford, England). 2006;22(22):2729-34.
45. Shastry BS. SNPs in disease gene mapping, medicinal drug development and evolution. Journal of human genetics. 2007;52(11):871-80.
46. Chaudhary R, Singh B, Kumar M, Gakhar SK, Saini AK, Parmar VS, et al. Role of single nucleotide polymorphisms in pharmacogenomics and their association with human diseases. Drug metabolism reviews. 2015;47(3):281-90.
47. Katara P. Single nucleotide polymorphism and its dynamics for pharmacogenomics. Interdisciplinary sciences, computational life sciences. 2014;6(2):85-92.
48. Alwi ZB. The Use of SNPs in Pharmacogenomics Studies. The Malaysian journal of medical sciences: MJMS. 2005;12(2):4-12.
49. Ahn TJ, Park K, Son DS, Huh N, Oh S, Bae T, et al. Selecting SNPs for pharmacogenomic association study. International journal of data mining and bioinformatics. 2012;6(5):521-34.
50. McCarthy JJ, Hilfiker R. The use of single-nucleotide polymorphism maps in pharmacogenomics. Nature biotechnology. 2000;18(5):505-8.
51. Lonetti A, Fontana MC, Martinelli G, Iacobucci I. Single Nucleotide Polymorphisms as Genomic Markers for High-Throughput Pharmacogenomic Studies. Methods in molecular biology (Clifton, NJ). 2016;1368:143-59.
52. Tenenbaum JD. Translational Bioinformatics: Past, Present, and Future. Genomics, proteomics & bioinformatics. 2016;14(1):31-41.
53. Vamathevan J, Birney E. A Review of Recent Advances in Translational Bioinformatics: Bridges from Biology to Medicine. Yearbook of medical informatics. 2017;26(1):178-87.
54. UniProt: the universal protein knowledgebase. Nucleic acids research. 2017;45(D1):D158-d69.
55. Sim NL, Kumar P, Hu J, Henikoff S, Schneider G, Ng PC. SIFT web server: predicting effects of amino acid substitutions on proteins. Nucleic acids research. 2012;40(Web Server issue):W452-7.
56. Capriotti E, Altman RB. Improving the prediction of disease-related variants using protein three-dimensional structure. BMC bioinformatics. 2011;12 Suppl 4:S3.
57. Choi Y, Sims GE, Murphy S, Miller JR, Chan AP. Predicting the functional effect of amino acid substitutions and indels. PloS one. 2012;7(10):e46688.
58. Calabrese R, Capriotti E, Fariselli P, Martelli PL, Casadio R. Functional annotations improve the predictive score of human disease-related mutations in proteins. Human mutation. 2009;30(8):1237-44.
59. Capriotti E, Fariselli P, Casadio R. I-Mutant2.0: predicting stability changes upon mutation from the protein sequence or structure. Nucleic acids research. 2005;33(Web Server issue):W306-10.
60. Cheng J, Randall A, Baldi P. Prediction of protein stability changes for single-site mutations using support vector machines. Proteins. 2006;62(4):1125-32.
61. Meyer MJ, Lapcevic R, Romero AE, Yoon M, Das J, Beltran JF, et al. mutation3D: Cancer Gene Prediction Through Atomic Clustering of Coding Variants in the Structural Proteome. Human mutation. 2016;37(5):447-56.
62. Ashkenazy H, Abadi S, Martz E, Chay O, Mayrose I, Pupko T, et al. ConSurf 2016: an improved methodology to estimate and visualize evolutionary conservation in macromolecules. Nucleic acids research. 2016;44(W1):W344-50.
63. Matsuo H, Kajihara M, Tomizawa D, Watanabe T, Saito AM, Fujimoto J, et al. Prognostic implications of CEBPA mutations in pediatric acute myeloid leukemia: a report from the Japanese Pediatric Leukemia/Lymphoma Study Group. Blood cancer journal. 2014;4:e226.
64. Tawana K, Rio-Machin A, Preudhomme C, Fitzgibbon J. Familial CEBPA-mutated acute myeloid leukemia. Seminars in hematology. 2017;54(2):87-93.
65. Mannelli F, Ponziani V, Bencini S, Bonetti MI, Benelli M, Cutini I, et al. CEBPA-double-mutated acute myeloid leukemia displays a unique phenotypic profile: a reliable screening method and insight into biological features. Haematologica. 2017;102(3):529-40.
66. Roberts SA, Gordenin DA. Clustered and genome-wide transient mutagenesis in human cancers: Hypermutation without permanent mutators or loss of fitness. BioEssays : news and reviews in molecular, cellular and developmental biology. 2014;36(4):382-93.
67. Harada H, Harada Y. Recent advances in myelodysplastic syndromes: Molecular pathogenesis and its implications for targeted therapies. Cancer science. 2015;106(4):329-36.
68. Pituch-Noworolska A. [Biological properties and sensitivity to induction therapy of differentiated cells expressing atypical immunophenotype in acute leukemia of children]. Folia medica Cracoviensia. 2001;42(3):5-80.
69. Grove CS, Vassiliou GS. Acute myeloid leukaemia: a paradigm for the clonal evolution of cancer? Disease models & mechanisms. 2014;7(8):941-51.
70. Haider M, Duncavage EJ, Afaneh KF, Bejar R, List AF. New Insight Into the Biology, Risk Stratification, and Targeted Treatment of Myelodysplastic Syndromes. American Society of Clinical Oncology educational book American Society of Clinical Oncology Annual Meeting. 2017;37:480-94.